Liquidity and Expected Returns: Lessons from Emerging Markets

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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 it significantly predicts 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 time 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 fully eliminated its impact. (*JEL* G12, G15, F30)

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 [e.g., Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Datar et al. (1998); Chordia et al. (2001b)]. Liquidity also predicts future returns and liquidity shocks are positively correlated with return shocks [see Amihud (2002); Jones (2002)]. Furthermore, if liquidity varies systematically [see Chordia et al. (2000); Huberman and Halka (2001)], securities with returns positively correlated with market liquidity should have high expected returns (see Pastor and Stambaugh (2003); Goyenko

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(2005); Martinez et al. (2005); Sadka (2006) for recent empirical work). Acharya and Pedersen (2005) develop a 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]

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 survey by Chuhan (1992), 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 period 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 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 United States 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 United States. 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 or market impact estimates, for example) are not

[1] There is a vast theoretical literature on liquidity that 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 et al. (2004); Eisfeldt (2004); Holmstrom and Tirole (2002); Huang (2003), and O'Hara (2003).

[2] Bekaert et al. (2002) show that many macroeconomic and financial time series show evidence of a break around such liberalizations.

widely available. For example, Domowitz et al. (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 et al. (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 first 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. For the period from the mid-1990s over which the Trade and Quote (TAQ) data are available, Goyenko et al. (2005) compare various transaction cost measures for U.S. data, and find that those based on observed zero returns are correlated with effective costs obtained from high-frequency data. In a longer historical context, we also provide a case study of how the measure compares to more standard liquidity measures using U.S. data. Our second measure incorporates information about the length of the non-trading (or zero return) interval.

Section 2 characterizes the dynamics of returns and liquidity using various vector autoregressions (VARs). We devote special attention to the hypotheses developed and tested in Amihud (2002) for U.S. data: if liquidity risk 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 return predictability (see Bekaert (1995) and Harvey (1995) for earlier work).

Section 3 outlines a simple pricing model that we use to interpret the liquidity effects on expected returns. The model accounts for both liquidity effects though transaction costs and for potential covariation of returns with systematic liquidity, and embeds the model in Acharya and Pedersen (2005) as a special case. We show that in such a model, local liquidity variables may affect expected returns even under full international 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.

1. Liquidity Measures for Emerging Markets

1.1 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 U.S. 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 et al. (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 1980s. 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

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

Table 1
Summary statistics January 1987–December 2003

	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
Std. dev.	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
Std. dev.	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
Std. dev.	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
Std. dev.	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

Table 1
(Continued)

	Argentina	Brazil	Chile	Colombia	Greece	India	Indonesia	Korea	Malaysia	Mexico	Pakistan	Philippines	Portugal	Taiwan	Thailand	Turkey	Venezuela	Zimbabwe	Average
Proportion of daily (local currency) zero returns in that month (ZR—value-weighted)																			
Mean	0.248	0.400	0.466	0.519	0.201	0.145	0.465	0.082	0.204	0.422	0.429	0.365	0.246	0.066	0.382	0.169	0.340	0.396	0.308
Std. dev.	0.215	0.159	0.120	0.128	0.141	0.042	0.159	0.033	0.118	0.247	0.200	0.116	0.128	0.043	0.109	0.099	0.200	0.171	0.135
Autocorrelation	0.967	0.801	0.941	0.892	0.956	0.799	0.956	0.773	0.943	0.986	0.953	0.906	0.937	0.899	0.901	0.906	0.909	0.772	0.900
Observations	192	168	174	144	192	168	165	204	204	192	149	196	192	196	204	192	167	132	180
Price pressure of non-trading (PP—value weighted)																			
Mean	0.584	0.709	0.730	0.764	0.361	0.375	0.776	0.239	0.338	0.665	0.704	0.658	0.644	0.158	0.626	0.371	0.568	0.663	0.552
Std. dev.	0.171	0.143	0.082	0.113	0.228	0.171	0.090	0.183	0.096	0.206	0.108	0.143	0.222	0.058	0.109	0.180	0.275	0.150	0.152
Autocorrelation	0.671	0.598	0.661	0.578	0.812	0.837	0.609	0.876	0.668	0.886	0.610	0.682	0.873	0.488	0.707	0.859	0.871	0.652	0.719
Observations	161	168	174	144	192	168	165	202	202	192	138	196	192	196	202	192	167	132	177
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 pressure 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 value-weighted proportion of zero daily returns and price pressure across all firms for the month. We also list the number of firms used in the computations.

each country, we calculate the capitalization-weighted 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 52% incidence of zero daily returns across domestically listed firms, and the smallest incidence of zero daily returns is 6.6%, on average, in Taiwan. Given the data limitations associated with the firm-level daily returns, we focus on a sample that covers January 1993 to December 2003.

Lengthly periods of consecutive non-trading days should be associated with greater illiquidity effects than non consecutive periods. 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 pressure of any trade following a 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 this return "catch-up" effect into account.[5]

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

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

where w_j represents the weighting of the stocks in the index. We use a capitalization-weighted measure, but we also compute an equally weighted price pressure measure as a robustness check. The variable, $\delta_{j,t}$, indicates no-trade days (as proxied by zero return days) and the first day after a no-trade interval when the price pressure is felt:

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

Also,

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

[4] We also construct equally weighted liquidity measures for each country. Moreover, we computed the zero measure using the Standard and Poor's EMDB daily data from 1996 to 2003. We find these alternative zero measures to be highly correlated with ours. The correlation with the equally weighted measure is reported in Table 2.

[5] We are grateful to Marco Pagano for comments that inspired the development of this measure. Ideally, we would also compute a true price impact measure using volume data, as proposed by Amihud (2002). Unfortunately, the quality and availability of volume data for emerging markets is so poor that this exercise proved futile.

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 $\mathrm{PP}_{i,t}$ may be drawn toward 1.0.

Our (il)liquidity measure is then $\mathrm{PP}_{i,t}$ averaged across all days in a particular month for each country. If no stocks trade at all, the measure is defined to be 1. Table 1 illustrates that the salient features of the data are very similar for the $\mathrm{PP}_{i,t}$ measure and the proportion of zero returns. The least liquid country is now Indonesia instead of Colombia. The first column of Table 2 shows that the two measures are generally highly correlated, with time-series correlations reaching as high as 95% for Venezuela. The average time-series correlation is 54%, but cross-sectionally the average zero and price pressure measures show 94% correlation. From these two measures, we create two liquidity proxies, $\ell n(1 - ZR)$ and $\ell n(1 - PP)$.

1.2 Do zeros measure illiquidity?

Liquidity and transactions costs are notoriously difficult to measure (see Stoll (2000); O'Hara (2003); Hodrick and Moulton (2005) 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 et al. (2000, 2001a, 2004) calculate daily measures of absolute and proportional bid–ask spreads, quoted share, and dollar depth. Unfortunately, such data are not generally available for emerging markets.

Amihud (2002) examines the average ratio of the daily absolute return to the dollar trading volume on that day. This absolute (percentage) price change per dollar of daily volume is interpreted as the daily price impact of order flow. Pastor and Stambaugh (2003) use a complex regression procedure involving daily firm returns and signed dollar volume to measure (innovations in) price reversals, both at the firm and market levels. Price reversals are viewed as reflecting illiquidity. 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 pressure measures. First, informationless trades (such as a trade by an index fund) should not give rise to price changes in liquid markets. The fact that we do not actually measure non-trading but only a zero return is consequently a potentially serious limitation. 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 2) across our sample countries is −0.35, indicating that the zeros measure is potentially reflecting relative *levels* of liquidity across the equity markets in our study. Table 2 presents correlations of our 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 −0.16. If positive volume zero returns do occur, we can still interpret zeros as a measure of the lack of informed trading (see Lesmond et al. (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.[6] The correlation is as often positive as it is negative, though economically small in most cases. On average, the correlation is effectively zero. Perhaps this is not so surprising, as alternative theories (e.g., 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 similar to French et al. (1987). First, we sum the squared returns at the *firm level* within the month, and then value-weight 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 country. On average, the average correlations between the proportion of zero daily returns and the price pressure measures with within-month volatility are −0.02 and −0.05, 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.

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

[6] We obtain estimates of the conditional volatility by maximum likelihood for both symmetric GARCH(1,1) and asymmetric threshold GARCH(1,1) models (see Glosten, Jaganathan, and Runkle (1993); Zakoian (1994)) of the measured monthly equity returns for each market. Table 2 only displays correlations for the threshold GARCH case.

Table 2
Correlations of percentage of zero daily returns (value-weighted) with alternative measures of liquidity

	Price pressure (*PP*)	Equal-weighted zero returns (*ZR*)	Turnover (*TO*)	TARCH conditional volatility	Within month volatility	Bid–ask spread	Correlation of bid–ask spread and turnover (*TO*)
Argentina	0.31	0.79	−0.01	0.45	0.16		
Brazil	0.36	0.32	−0.06	0.13	0.15	0.09	0.06
Chile	0.65	0.83	−0.15	−0.12	−0.02		
Colombia	0.58	0.52	−0.34	0.29	−0.01		
Greece	0.67	0.63	−0.43	−0.69	−0.17		
India	0.37	0.73	−0.28	−0.02	−0.01		
Indonesia	−0.23	0.06	0.41	0.30	0.02	0.24	−0.05
Korea	0.84	0.79	−0.57	0.08	−0.02	0.66	−0.25
Malaysia	0.72	0.94	−0.12	−0.12	−0.18	0.52	−0.54
Mexico	0.80	0.80	−0.30	−0.08	−0.16	0.87	−0.09
Pakistan	0.54	0.31	0.42	0.58	0.18		
Philippines	0.73	0.68	−0.21	−0.26	−0.31	0.15	−0.33
Portugal	0.54	0.56	−0.65	−0.25	−0.16	0.27	−0.19
Taiwan	0.38	0.52	−0.19	−0.08	−0.14		
Thailand	0.56	0.65	−0.37	0.34	−0.13	0.82	−0.59
Turkey	0.35	0.53	0.34	0.15	−0.08	0.66	0.19
Venezuela	0.95	0.95	−0.62	−0.03	−0.05		
Zimbabwe	0.66	0.46	0.22	0.24	0.07		
Cross-sectional correlation	0.94		−0.35				
Time-series correlation	0.54	0.62	−0.16	0.05	−0.05	0.48	−0.20

For each country, we calculate the value-weighted proportion of zero daily returns (*ZR*) and price pressure of non-trading (*PP*) 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). 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 an asymmetric threshold GARCH(1,1) (TARCH). Following French et al. (1987), within-month volatility is constructed by first summing the squared returns for each firm within the month, and then averaging across value-weighted firms for that month. The time series correlation simply averages the time-series correlations across countries, whereas the cross-sectional correlation is the cross-sectional correlation between the time-series averages for the two measures.

to markets with larger stocks. The focus on a value-weighted measure mitigates this concern. Moreover, there is a strong negative cross-sectional correlation between the number of companies used in the computation and both the equal or value-weighted proportion of daily zero returns. The cross-sectional correlation between the number of firms covered by Datastream and the value-weighted zeros measure is −0.64 (see Table 1).

Perhaps the most compelling diagnostic is to explore the relation between the returns-based measure of transaction costs and more conventional 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 1990s for a few countries from the Datastream research files. We find that the proportion of daily zero returns measure is highly correlated, 48% 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 -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 (2006), and Levine and Schmukler (2006) 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 pressure measures excluding any firms that are also listed in the United States by means of an ADR according to Datastream. The resulting measures are very highly correlated with our original measures, with the correlation exceeding 0.95 in almost every case.

1.3 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 (1984) model.[7] 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 on high-frequency Trade and Quote (TAQ) data are typically above 0.90 for individual securities in overlapping samples. Hasbrouck (2005) argues that Hasbrouck (2004) effective cost and Amihud (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 1(a) 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 frequency from 1962 to 2001. The correlations 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 five 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 (2002) in Figure 1(a). Interestingly, unlike the other measures of transaction costs, the proportional spread data do exhibit sharp declines in the late 1990s in accordance with the reduced incidence of zero daily returns. The overall correlation between bid–ask spreads and the proportion of zeros is 0.30. 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 United States, we can actually construct a no-volume zeros measure. Figure 1(b) 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 United States 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 (2003) (PS). For the PS

[7] Also see Harris (1990) for an analysis of the Roll estimator, and Ghysels and Cherkaoui (2003) for an application to an emerging market.

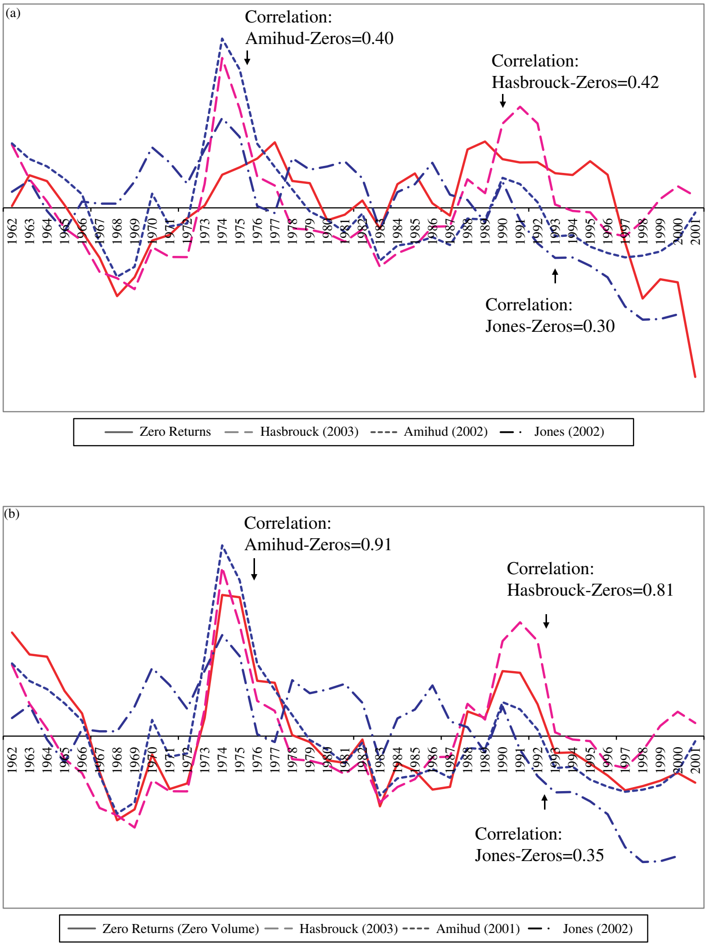

Figure 1
(a) Comparison of Transaction Costs/Liquidity Measures using U.S. Data; (b) Comparison of Transaction Costs/Liquidity Measures using U.S. Data: Zero Volume. Note the y-axis is not labeled because all variables are standardized.

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 each another and only the first method leads to correlations with Hasbrouck (2005) effective costs, Amihud (2002) price impact measure, and measured bid–ask spreads that have the expected sign. The PS 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.[8]

2. Liquidity and Expected Asset Returns: A VAR Analysis

If excess returns reflect compensation for expected market illiquidity and illiquidity is persistent, measures of liquidity should predict returns with a negative sign. Moreover, 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 raises prices. Amihud (2002) formulates these hypotheses and finds support for them in U.S. data. In this section, we estimate simple VAR systems that allow us to test these hypotheses for emerging markets. The benchmark specification distinguishes between local and global liquidity, and examines the effect of equity market openness on the return-liquidity relation. In subsequent specifications, we consider a number of other country-level characteristics and investigate potential contagion effects.

In the next section, we propose 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 nests 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.

2.1 VAR benchmark specification

For our benchmark specification, we define the liquidity measure $L_{i,t} = \ln(1 - ZR_{i,t})$, with $ZR_{i,t}$ the value-weighted zero return measure

[8] 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).

for country i in month t. Also, define $r_{i,t}$, the value-weighted 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 $[r_{i,t}, L_{i,t}]$. Below, we consider various alternative specifications. For country i, the base VAR(1) model is as follows:

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

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 Jong and De Roon (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 the ratio of the market capitalization of the constituent firms comprising the S&P-IFC Investable Index to that of firms comprising 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 represents a portfolio of domestic equities that are available to foreign investors. The investability measure varies between 0 (closed market) and 1 (fully open market). If capital market regulations truly affect the degree of capital market integration, $Lib_{i,t}$ 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 (e.g., 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, $\mathbf{\Sigma}_{i,t}^{1/2}$, 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 semidefinite. 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. Within this framework, the Amihud (2002) hypotheses are easily tested. For a closed equity market, this implies that the (1,2) element in $\mathbf{A}_0$ is negative and the (2,1) element in $\mathbf{\Sigma}_0$ is positive. Our framework then permits tracing the effect of open equity markets on the pricing of liquidity.

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 Equations (4) and (5) for each country as follows:

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

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:

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

Here, $diag(\cdot)$ takes the U.S. variance-covariance matrix, but zeros out the off-diagonal elements. Accordingly, $\boldsymbol{\beta}_{i,t} = \boldsymbol{\beta}_0 + Lib_{i,t}\boldsymbol{\beta}_1$ 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, $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_1$, 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.

2.2 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 the full panel can be expressed as follows:

$$L = \sum_{t=1}^{T} l_t = -\frac{k \cdot (N+1)}{2} \ln(2\pi) - \sum_{t=1}^{T} \left(\frac{1}{2} \ln |\mathbf{\Omega}_{t-1}| + \frac{1}{2} \boldsymbol{\epsilon}_t' \mathbf{\Omega}_{t-1}^{-1} \boldsymbol{\epsilon}_t \right), \quad (8)$$

where k is the number of endogenous variables, and $k \cdot (N+1)$ is the number of individual equations. For a base specification of two variables, this involves 39 parameters (excluding country fixed effects). 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, such as in Stambaugh (1999) and Hodrick (1992). The results in that literature, however, are not directly applicable to our framework because we have a panel setup. 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.

We simulate series $\tilde{\mathbf{x}}_{i,t} = [r_{i,t}, L_{i,t}]$ according to the base VAR(1) model described in Equations (4) and (5) with the errors drawn from the standard normal distribution. For $Lib_{i,t}$, we use the observed liberalization indicators, and we constrain the first row of $\mathbf{A}_0$, $\mathbf{A}_1$, $\mathbf{B}_0$, $\mathbf{B}_1$, and $\mathbf{A}_w$ to be a row of zeros, so that under the null hypothesis, lagged endogenous variables *do not* predict returns for emerging markets or the United States. The innovation covariance matrix is as in Equation (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 simulation focus is 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 Equation (8). We also consider a simulation under the alternative of return

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	−0.012	0.937	−0.270	0.014*
Brazil	−0.034	0.471	0.036	<0.001*
Chile	0.047	0.770	−0.217	0.042*
Colombia	0.260	0.027*	−0.210	0.060
Greece	−0.088	0.617	0.199	0.022*
India	0.045	0.034*	0.371	<0.001*
Indonesia	0.177	0.073	−0.063	0.355
Korea	0.038	0.912	0.114	0.002*
Malaysia	0.078	0.015*	0.061	0.089
Mexico	0.092	0.754	0.118	0.263
Pakistan	−0.077	0.781	0.104	0.537
Philippines	0.143	0.377	−0.052	0.407
Portugal	0.027	0.729	0.261	<0.001*
Taiwan	−0.058	0.385	−0.109	0.120
Thailand	0.034	0.137	0.083	<0.001*
Turkey	−0.066	0.472	−0.065	0.309
Venezuela	−0.166	0.254	−0.093	0.576
Zimbabwe	−0.047	0.857	−0.339	0.002*
Joint test (all countries)		0.950		<0.001*
United States	0.003	0.841	−0.262	0.028*

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 $18 \times 3 = 54$ restrictions); asymptotic p-values are reported. *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.

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. Under the null of no predictability, the mean coefficient is −0.0009, and the t-statistic is −0.05, so that there is essentially no estimation bias for the observed liquidity effect. The distribution of the t-statistic is similarly quasi unbiased, meaning that for a two-sided test at the 5% level of significance, the critical value is −2.03. Our tests also have satisfactory power for a test of the null hypothesis of liquidity not predicting future returns. Given these results, we will use asymptotic p-values for the remainder of the article, as we have generally verified that our results are robust to finite sample inference.

2.3 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 also present asymptotic p-values, country by country, for a Wald test that the first three autocorrelations are jointly zero. The first-order autocorrelation coefficient of the return residuals is above 0.2 for only one country (Colombia) and, using the asymptotic test and Monte Carlo-based critical values, we only reject the null of no serial correlation for three countries (at the 5% level). The model is less successful with respect to liquidity. There are six countries with residual autocorrelation coefficients over 0.2 in absolute value, with the autocorrelation coefficient close to 0.4 for India. Both the asymptotic and Monte Carlo-based tests reject the null of no autocorrelation for nine countries at the 5% level. 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. The specification tests results are robust to the inclusion of additional instruments, such as market turnover or the dividend yield.

Using the standard Jarque–Bera normality test, we not surprisingly reject the normality of both the return and liquidity residuals for the majority of the countries. This reconfirms the usefulness of standard errors robust to the mis-specification of the error distribution.

2.4 Empirical results

2.4.1 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 much affected by the financial openness regime. The return coefficient on lagged local liquidity (in closed markets) is statistically significant, −0.1321 (with a standard error of 0.030); however, the coefficient becomes much less negative in financially open markets, and the change is significant. Hence, we confirm Amihud (2002) results for closed markets, but not for open 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

Table 4
Vector autoregression of returns and liquidity (value-weighted) 1993–2003

A. VAR dynamics:

	Closed	Estimate	Standard error		Open	Estimate	Standard error
$\mathbf{A}_0$				$\mathbf{A}_1$			
R_t	R_{t-1}	0.0548	*0.0422*	R_t	R_{t-1}	−0.0184	*0.0550*
	L_{t-1} (ZR)	−0.1321	*0.0302*		L_{t-1} (ZR)	0.1255	*0.0353*
L_t (ZR)	R_{t-1}	0.0296	*0.0392*	L_t (ZR)	R_{t-1}	0.0281	*0.0504*
	L_{t-1} (ZR)	0.6415	*0.0275*		L_{t-1} (ZR)	0.2389	*0.0319*
$\mathbf{B}_0$				$\mathbf{B}_1$			
R_t	$R_{w,t-1}$	0.2174	*0.1411*	R_t	$R_{w,t-1}$	−0.0141	*0.1712*
	$L_{w,t-1}$ (ZR)	−0.4416	*0.1736*		$L_{w,t-1}$ (ZR)	0.4041	*0.2265*
L_t (ZR)	$R_{w,t-1}$	0.2426	*0.1685*	L_t (ZR)	$R_{w,t-1}$	−0.1593	*0.2057*
	$L_{w,t-1}$ (ZR)	−0.8979	*0.1564*		$L_{w,t-1}$ (ZR)	0.5369	*0.1964*
$\boldsymbol{\alpha}_1$							
R_t	Lib_{t-1}	0.0805	*0.0321*				
L_t (ZR)	Lib_{t-1}	0.1835	*0.0289*				
B. U.S. VAR dynamics:							
$\mathbf{A}_w$				$\boldsymbol{\Sigma}_w$			
$R_{w,t}$	$R_{w,t-1}$	0.0085	*0.0805*		c_{11}(Returns)	0.0396	*0.0025*
	$L_{w,t-1}$ (ZR)	−0.0974	*0.0710*		c_{21}(Returns and L)	−0.0013	*0.0008*
$L_{w,t}$ (ZR)	$R_{w,t-1}$	0.0226	*0.0191*		$c_{22}(L)$	0.0084	*0.0005*
	$L_{w,t-1}$ (ZR)	0.9876	*0.0155*				
C. Cholesky decomposition of variance-covariance matrix:							
$\boldsymbol{\Sigma}_0$	c_{11}(Returns)	0.1554	*0.0042*	$\boldsymbol{\Sigma}_1$	c_{11}(Returns)	−0.0511	*0.0051*
	c_{21}(Returns and L)	0.0331	*0.0059*		c_{21}(Returns and L)	−0.0251	*0.0071*
	$c_{22}(L)$	0.1404	*0.0044*		$c_{22}(L)$	−0.0498	*0.0054*
D. Exposures to world shocks:							
β_0				β_1			
R_t	$R_{w,t}$	0.3430	*0.1830*	R_t	$R_{w,t}$	0.9112	*0.2226*
L_t (ZR)	$R_{w,t}$	0.0786	*0.0618*	L_t (ZR)	$R_{w,t}$	−0.0656	*0.0792*
R_t	$L_{w,t}$ (ZR)	−0.6947	*0.7163*	R_t	$L_{w,t}$ (ZR)	−0.3026	*1.1200*
L_t (ZR)	$L_{w,t}$ (ZR)	−0.4990	*0.6971*	L_t (ZR)	$L_{w,t}$ (ZR)	0.9084	*0.8942*

Return predictability local instruments	Wald Test	p-value	Return predictability world instruments	Wald Test	p-value
Closed	20.58	0.0000	Closed	9.64	0.0081
Open	1.98	0.3724	Open	2.86	0.2388
Change in predictability	62.23	0.0000	Change in predictability	10.38	0.0344

This table presents bivariate VAR maximum likelihood estimates, including excess returns and 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 $\Sigma_0 + \text{Lib}_{it}\Sigma_1$, where c_{ij} denotes the i,jth element of these two lower triangular matrices. We present Bollerslev and Wooldridge (1992) robust standard errors. In November 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.

Finally, we present several Wald tests on return predictability. For the first tests on return predictability from local instruments, the null hypothesis is that the first row of $A_0 = 0$ under segmentation and the first row of $A_0 + A_1 = 0$ under integration. For the tests on return predictability from global instruments, the null hypothesis is that the first row of $B_0 = 0$ under segmentation and the first row of $B_0+B_1 = 0$ 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 chi-square distributions under the null with 2 degrees of freedom.

positively 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 0.0548 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, but we find the average autocorrelation coefficient to be lower (0.048), not higher. As a result, it seems unlikely that non-trading is the main 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 $\mathbf{A}_0$ is zero for closed countries and the first row of $\mathbf{A}_0 + \mathbf{A}_1$ is zero for open countries. For closed countries, the test rejects the null hypothesis of no predictability with a p-value of 0.00; however, for open countries, the test fails to reject (p-value of 0.37). For the tests on return predictability using global factors, the null hypothesis is that the first row of $\mathbf{B}_0$ is zero for closed countries and the first row of $\mathbf{B}_0 + \mathbf{B}_1$ is zero for open countries. Surprisingly, the test rejects for closed countries, but not for open countries. We also investigate the effects of financial liberalization on return predictability by testing the null hypotheses that the first rows of $\mathbf{A}_1$ and $\mathbf{B}_1$ are 0. Both hypotheses are rejected at the 5% level.

Turning to the liquidity equations, we see that the liquidity variable displays significant autocorrelation, with an estimated coefficient on lagged liquidity of 0.64, with the coefficient increasing to 0.88 for financially open countries. Lagged returns positively affect future liquidity with the coefficient becoming larger for open countries. Griffin et al. (2004) examine the relation between past returns and future trading activity in 45 countries, measured by turnover, and find a positive and significant effect. Interestingly, a detailed analysis of their results reveals that the effect is less pronounced for some more developed markets and nonexistent for the United States (at least over the full sample). We also find that the effect is not significant for the United States. 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.

Next, we examine how U.S. returns and liquidity affect local variables, the B matrices. A 1% increase in U.S. market returns predicts a 22 basis point increase in local returns in closed 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, but the effect is dramatically reduced upon liberalization. Global liquidity also affects local returns negatively and the effect is significant, but disappears altogether for liberalized countries. This result is not robust across specifications with different return or liquidity measures.

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. If liberalizations reduce the cost of capital, we would expect a negative coefficient in the return equation, but we find a positive and significant coefficient. Bekaert and Harvey (2000) discuss extensively the difficulty in interpreting liberalization effects based on return measures in emerging markets. In the liquidity equation, liberalizations significantly improve liquidity, as we would expect.

We also present evidence on the U.S. market VAR dynamics. Market returns in the United States do not display economically or statistically significant autocorrelation. Further, while the return predictability coefficient on lagged liquidity is large and negative, it is not statistically significantly different from zero. 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. When a longer sample is used going back to 1962, the autocorrelation drops considerably. A Wald test of the null hypothesis that the U.S. dynamics are equivalent to the VAR dynamics of a fully integrated emerging market, $\mathbf{A}_w^{i,j} = \mathbf{A}_0^{i,j} + \mathbf{A}_1^{i,j}$, for every (i, j), 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 closed markets (the off-diagonal element for $\mathbf{\Sigma}_0$). It is significantly reduced by the liberalization state (the off-diagonal element for $\mathbf{\Sigma}_1$), but remains positive. 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 (2002) hypotheses that liquidity risk is priced. In both cases, this is more pronounced in markets with lower levels of foreign investability. 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 $\mathbf{\Sigma}_1^{i,j} = 0$ for every (i, j) is sharply rejected with a p-value of less than 0.01. For the U.S. market equations, we find c_{21} to be negative, but it is not significantly different from zero.

Finally, we present evidence on the contemporaneous covariances between local and U.S. shocks. In closed markets, the beta reflecting the covariance between U.S. and local returns is positive but not significant; however, as the degree of investability increases, the beta becomes highly significant, and exceeds 1. The majority of the other beta coefficients are not statistically significant, and we do not discuss them further.

In sum, the bivariate VAR of local returns and value-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. These results are also preserved in (unreported) country-by-country VARs, with only the shock covariance estimates being statistically significant. Moreover, local sources of predictability are stronger than global sources.

2.4.2 VARs with alternative liquidity measures. Table 5 investigates the robustness of our results across liquidity measures. We report results for bivariate VARs including (value-weighted) returns and four different liquidity measures based on the following: (1) equally-weighted zero returns, (2) the equally-weighted price pressure based measure, (3) the value-weighted price pressure measure, and (4) turnover. We report and discuss only the salient features of the dynamics.

First, we investigate the Amihud (2002) hypotheses. The coefficient on past liquidity in the return equation is consistently negative. The coefficient is statistically significant in every case, except for the equally weighted price pressure measure. Consistent with the benchmark case, the coefficients are much smaller for liberalized countries and no longer statistically significant. 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. Furthermore, we always observe a positive and significant correlation between return and liquidity shocks, which is weaker for open markets. The exception is for the equally-weighted price pressure measure where the correlation is insignificant for closed countries but strengthens for open markets.

While we do not report the U.S. dynamics, we find consistently negative coefficients on past liquidity in the return equation, but the coefficients are mostly not significant. Moreover, we fail to find a positive correlation between return and liquidity shocks, confirming that it is harder to find liquidity effects for well-developed markets. When we use an arguably higher quality liquidity measure, based on the zero-volume, zero-returns, we find the opposite: an unexpected positive but insignificant predictability effect and an expected positive and significant correlation between return and liquidity shocks.

Table 5
VARs for returns and alternative liquidity measures 1993–2003

Liquidity measure	Amihud hypotheses										
	A_0	A_1	Σ_0	Σ_1	A_0	A_1	B_0	B_1	α_1	β_0	β_1
	$[R_{i,t}, L_{i,t-1}]$	$[R_{i,t}, L_{i,t-1}]$	c_{21}	c_{21}	$[L_{i,t}, R_{i,t-1}]$	$[L_{i,t}, R_{i,t-1}]$	$[R_{i,t}, L_{w,t-1}]$	$[R_{i,t}, L_{w,t-1}]$	$[L_{i,t}, Lib_{t-1}]$	$[R_{i,t}, R_{w,t-1}]$	$[R_{i,t}, R_{w,t-1}]$
L_t (ZR) value-weighted	−0.1321	0.1255	0.0331	−0.0251	0.0296	0.0281	−0.4416	0.4042	0.1835	0.3430	0.9112
	(0.0302)	*(0.0354)*	*(0.0059)*	*(0.0072)*	*(0.0393)*	*(0.0506)*	*(0.1736)*	*(0.2272)*	*(0.0289)*	*(0.1829)*	*(0.2224)*
L_t (ZR) equal-weighted	−0.0531	0.0316	0.0277	−0.0041	0.1144	−0.0463	−0.0535	0.0441	−0.0270	0.3101	0.9111
	(0.0200)	*(0.0254)*	*(0.0043)*	*(0.0056)*	*(0.0287)*	*(0.0402)*	*(0.0834)*	*(0.1135)*	*(0.0271)*	*(0.1822)*	*(0.2180)*
L_t (PP) value-weighted	−0.0323	0.0263	0.0415	−0.0286	0.0209	0.1962	−0.0520	0.0433	0.1664	0.3745	0.8869
	(0.0130)	*(0.0158)*	*(0.0138)*	*(0.0186)*	*(0.0915)*	*(0.1350)*	*(0.0651)*	*(0.0874)*	*(0.0647)*	*(0.1809)*	*(0.2169)*
L_t (PP) equal-weighted	−0.0177	0.0070	0.0013	0.0271	0.0390	0.1395	−0.0095	0.0150	−0.0853	0.3792	0.8521
	(0.0150)	*(0.0186)*	*(0.0086)*	*(0.0117)*	*(0.0560)*	*(0.0841)*	*(0.0377)*	*(0.0499)*	*(0.0511)*	*(0.1864)*	*(0.2257)*
L_t (TO) turnover	−0.0017	0.0021	0.0712	0.0019	0.2968	−0.2449	0.0107	−0.0177	−0.1426	0.2962	0.9512
	(0.0059)	*(0.0074)*	*(0.0226)*	*(0.0282)*	*(0.1315)*	*(0.1731)*	*(0.0235)*	*(0.0310)*	*(0.0866)*	*(0.1854)*	*(0.2237)*

This table presents selected coefficients from bivariate VAR maximum likelihood estimates, including excess returns and L. In contrast to the benchmark case presented in Table 4, we consider four alternative liquidity measures: equal-weighted zero return, value-weighted price pressure, equal-weighted price pressure, and equity market turnover. 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_{21} denotes the element associated with the contemporaneous return-liquidity relation. We present Bollerslev and Wooldridge (1992) robust standard errors in parentheses.

Given that equity market turnover is a natural measure for local market trading activity, we also consider a specification that includes total equity market turnover. Neither lagged local, nor U.S. equity market turnover significantly predict future excess returns. However, there appears to be a strong positive contemporaneous relation between return and turnover shocks for segmented countries, which is relatively unaffected by the liberalization state. Hence, there is some evidence of a priced liquidity effect. Nevertheless, when we include both turnover and the zeros measure in a trivariate VAR (not reported), the zeros measure retains strong independent pricing effects. Consequently, the zero return-based measures may capture features of market liquidity and transaction costs not related to equity market turnover.

Second, the predictive power of returns for future liquidity in closed markets is only significant for the equally weighted zeros-based measure and for turnover, but the coefficient is overall positive, consistent with the evidence presented in Griffin et al. (2004). Interestingly, for liberalized markets, the coefficient becomes more positive for all measures, except for the equally weighted zeros measure and for turnover.

Third, we also report the effect of liberalization on the unconditional averages. For returns, the effects are not robust across measures, and are not statistically significant. For liquidity, the value-weighted measures show significant improvements in liquidity post-liberalization, whereas the equally weighted measures show insignificantly negative coefficients.

Fourth, 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 closed countries and rises by about 0.85–0.90 for a fully liberalized country.

2.4.3 Incorporating dividend yields in the VAR. 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 risk 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 L 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., Engstrom (2003); Goyal and Welch (2003); Ang and Bekaert (2007)] 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.

Table 6 reports a subset of the VAR dynamics for a trivariate VAR incorporating dividend yields, while repeating our benchmark VAR results. First, 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. The inclusion of the dividend yield slightly increases the parameter associated with the predictability of returns from lagged liquidity, but it remains negative and statistically significant. If dividend yields and liquidity are negatively correlated, the trivariate coefficient on liquidity should indeed be smaller than the bivariate coefficient we report above. Conversely, because dividend yield variation partially reflects variation in liquidity, it is not surprising to find the coefficient on the dividend yield is higher (0.0933) and significantly different from zero in a univariate regression of returns on the dividend yield (not reported). 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.

The contemporaneous covariance between liquidity and dividend yield shocks reported in Table 6 is indeed negative and highly significant for closed 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.

As in the bivariate case, we also present several Wald tests on return predictability. Recall, the null hypotheses are that the first row of $\mathbf{A}_0$ is 0 for closed countries and the first row of $\mathbf{A}_0 + \mathbf{A}_1$ is 0 under financial openness, when local instruments are considered. As in the bivariate case, the first test rejects the null of no predictability with a p-value of 0.002. The null hypothesis of no return predictability from local factors under openness is not rejected at the 5% level. As in the bivariate case, we surprisingly find evidence of return predictability using global factors only for closed countries.

Of course, it is possible that dividend yields also embed information about cash flows, and controlling for predictable variation in cash flows may alter our results.[9] To investigate this, we obtain dividend growth rates for all of the countries in the sample. We measure dividends paid out over the previous year in each month for each country. The dividend growth measure is the monthly log difference of this variable. We add lagged and contemporaneous dividend growth to all three equations (for returns, liquidity, and dividend yields) in the VAR, and re-estimate the system.

[9] Loderer and Roth (2005) examine the effect of liquidity on price–earnings ratios in a cross-sectional context, controlling for earnings growth.

Table 6
Alternative VAR specifications for returns, liquidity, and dividend yields 1993–2003

Dependent variable: R_t	Benchmark	Trivariate	Dependent variable: R_t	Benchmark	Trivariate
$\mathbf{A}_0$			$\mathbf{A}_1$		
L_{t-1} (ZR)	−0.1321	−0.1118	L_{t-1} (ZR)	0.1255	0.1140
	(0.0302)	*(0.0361)*		*(0.0353)*	*(0.0450)*
DY_{t-1}		0.0397	DY_{t-1}		−0.0005
		(0.0679)			*(0.0995)*
Dependent variable: R_t			**Dependent variable: R_t**		
$\mathbf{B}_0$			$\mathbf{B}_1$		
$R_{w,t-1}$	0.2174	0.2521	$R_{w,t-1}$	−0.0141	−0.0673
	(0.1411)	*(0.2029)*		*(0.1712)*	*(0.2491)*
$L_{w,t-1}$ (ZR)	−0.4416	−0.2359	$L_{w,t-1}$ (ZR)	0.4041	0.7276
	(0.1736)	*(0.5476)*		*(0.2265)*	*(0.6943)*
$DY_{w,t-1}$		0.2521	$DY_{w,t-1}$		0.5270
		(0.5965)			*(0.7755)*
Dependent variable: DY_t			**Dependent variable: DY_t**		
$\mathbf{A}_0$			$\mathbf{A}_1$		
R_{t-1}		−0.0160	R_{t-1}		0.0224
		(0.0179)			*(0.0256)*
L_{t-1} (ZR)		−0.0173	L_{t-1} (ZR)		0.0126
		(0.0134)			*(0.0166)*
DY_{t-1}		0.9152	DY_{t-1}		−0.0025
		(0.0185)			*(0.0254)*
Cholesky decomposition of variance-covariance matrix:					
$\mathbf{\Sigma}_0$			$\mathbf{\Sigma}_1$		
(Returns and L)	0.0331	0.0328	(Returns and L)	−0.0251	−0.0222
	(0.0059)	*(0.0059)*		*(0.0071)*	*(0.0070)*
(Returns and DY)		−0.0164	(Returns and DY)		−0.0061
		(0.0024)			*(0.0030)*
(L and DY)		−0.0127	(L and DY)		0.0134
		(0.0026)			*(0.0033)*

Table 6
(Continued)

Dependent variable: R_t	Benchmark		Trivariate		Dependent variable: R_t	Benchmark		Trivariate	
Local return exposures to world shocks:									
β_0					β_1				
$R_{w,t}$	0.3430		−0.2480		$R_{w,t}$	0.9112		0.7336	
	(0.1830)		*(0.1663)*			*(0.2226)*		*(0.2084)*	
$L_{w,t}$	0.0786		−0.2078		$L_{w,t}$	−0.0656		0.1739	
	(0.0618)		*(2.5190)*			*(0.0792)*		*(3.2560)*	
$DY_{w,t}$			−0.1106		$DY_{w,t}$			0.0550	
			(1.7400)					*(0.3398)*	
Return predictability local instruments	Wald Tests				Return predictability world instruments	Wald Tests			
Closed	20.58	0.00	19.45	0.00	Closed	9.64	0.01	10.55	0.04
Open	1.98	0.37	1.12	0.76	Open	2.86	0.24	5.17	0.00
Change in predictability	62.23	0.00	94.17	0.00	Change in predictability	10.38	0.03	38.63	0.46

This table presents maximum likelihood estimates for two alternative VAR specifications: our benchmark bivariate VAR including excess returns and L and a trivariate VAR including excess returns, L, and dividend yields (multiplied by 100). 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. We parameterize the Cholesky decomposition of the VAR innovation covariance as $\Sigma_0 + \text{Lib}_{it}\Sigma_1$, where c_{ij} denotes the i,jth element of these two lower triangular matrices.

We highlight the contemporaneous relation between returns, L, and dividend yields (plus dividend yields with L), which are assumed to differ across liberalization state. We also present Bollerslev and Wooldridge (1992) robust standard errors below each estimate in parentheses. 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 $B_0 = 0$ under segmentation and the first row of $B_0 + B_1 = 0$ 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 chi-squared distributions under the null with 2 (bivariate) or 3 (trivariate) degrees of freedom.

Fortunately, incorporating dividend growth rates in the regressions does not affect the results (available upon request). The critical coefficients regarding the pricing of liquidity remain almost unaltered. Dividend growth itself generates very few significant coefficients. However, past dividend growth does significantly and positively predict future dividend yields, suggesting that the regression is both controlling for predictable variation in cash flows and leaving the inference regarding liquidity and expected returns generally unaffected.

2.4.4 Alternative interaction effects. In the main results, we explore the effects of global market integration on the pricing of liquidity where the effects are otherwise constrained to be the same across countries of similar levels of financial openness. However, there may be reasons other than the level of financial openness why the pricing of liquidity differs across countries. In this section, we explore a number of alternative interaction effects. The results are summarized in Table 7.

The first setup we examine is one of regional integration rather than global market integration. Here, we replace the U.S. variables by variables for regional indices. We investigate both a Latin American and a Southeast Asian value-weighted index in two different specifications. The degree of openness index is now simply a dummy variable that indicates whether the country belongs to that region or not.[10] For local predictability, this implies that we simply distinguish regional effects in liquidity pricing. The results for $\mathbf{A}_0$ and $\mathbf{A}_1$ in Table 7 suggest that liquidity significantly predicts returns with a coefficient of -0.0238, with the effect more pronounced for Southeast Asian countries as the coefficient becomes marginally more negative. However, the difference is not significant. For Latin America, the regional effect is stronger, in that the coefficient is significantly less negative for Latin American countries ($\mathbf{A}_{1,12}$ is 0.0508). The **B**-matrices capture potential "contagion" effects outside the region: does liquidity in one region have an effect on returns in other emerging markets. Surprisingly, we find that the predictability effects of Southeast Asian liquidity for local market returns are smaller for countries within the region, but these coefficients are not statistically significant. For the Latin American specification, there is no significant regional effect either. When we look at liquidity pricing in the shocks, we find that for countries outside our regions there is a strong and significantly positive correlation between liquidity and return shocks. However, the effect is weaker for both Southeast Asian and Latin American countries, and significantly so in the former case. Finally, local returns are significantly predicted by

[10] Notice that we cannot identify a mean effect of belonging to the region or not because of the presence of fixed effects.

Table 7
VARs: alternative interaction effects 1993–2003

	Amihud hypotheses					
	A_0	A_1	Σ_0	Σ_1	B_0	B_1 [in region]
Interaction	$[R_{i,t}, L_{i,t-1}]$	$[R_{i,t}, L_{i,t-1}]$	c_{21}	c_{21}	$[R_{i,t}, L_{c,t-1}]$	$[R_{i,t}, L_{c,t-1}]$
East Asia	−0.0238	−0.0084	0.0237	−0.0140	−0.1810	0.1005
	(0.0123)	*(0.0265)*	*(0.0033)*	*(0.0040)*	*(0.1322)*	*(0.1806)*
Latin America	−0.0604	0.0508	0.0192	−0.0006	−0.0029	0.0163
	(0.0196)	*(0.0237)*	*(0.0026)*	*(0.0053)*	*(0.0247)*	*(0.0286)*
Low/high liquidity level	−0.0534	0.0324	0.0244	−0.0091	−0.2232	0.1742
	(0.0153)	*(0.0272)*	*(0.0070)*	*(0.0090)*	*(0.1086)*	*(0.1200)*
Law and order	−0.0804	0.0696	0.0413	−0.0407	−0.5937	0.5402
	(0.0327)	*(0.0500)*	*(0.0093)*	*(0.0127)*	*(0.2629)*	*(0.3429)*
Political risk	−0.1460	0.1832	0.0576	−0.0640	−1.3100	1.6980
	(0.0599)	*(0.0854)*	*(0.0107)*	*(0.0132)*	*(0.4454)*	*(0.6149)*

This table presents selected coefficients from bivariate VAR maximum likelihood estimates, including excess returns and L. In contrast to the benchmark case, presented in Table 4, where the VAR coefficients are interacted with financial openness, we interact the coefficients with five different interaction variables: two regional indicators for either East Asia or Latin America, an indicator separating countries into below or above median liquidity levels, and the ICRG's law and order and composite political risk indices (scaled to range from 0 to 1 where larger values denote better law and order or less political risk). For the regional regressions, the U.S. variables are replaced by East-Asian or Latin American variables, respectively.

We include the lagged U.S. return, lagged U.S. liquidity, and the lagged interaction indicator as additional exogenous variables, as well as fixed effects (not reported). For the regional and low/high liquidity level indices, we include only the first two. We parameterize the Cholesky decomposition of the VAR innovation covariance as $\Sigma_0 + z_{it}\Sigma_1$, where c_{21} denotes the element associated with the contemporaneous return-liquidity relation and z_{it} represents one of the interaction variables. We present Bollerslev and Wooldridge (1992) robust standard errors in parentheses

regional returns, but surprisingly this is true for all countries, not just those countries within the region.

A second obvious interaction variable is the level of transaction costs. We model this with a dummy variable that is one when the country has below median transaction costs. Hence, here we test for a relationship between the average level of liquidity and liquidity pricing. The results are on the third line of Table 7. The results are as expected: countries with lower transaction costs on average display a weaker predictability effect and weaker shock correlation. Nevertheless, the difference in coefficients is not significant in either case.

Third, it is conceivable that the concentration of ownership may play a role in the liquidity of a stock market. La Porta et al. (2000), among others, argue that ownership concentration is negatively correlated with the quality of corporate governance and more generally the legal system. We use a subindex of the ICRG political risk ratings, namely law and order, to proxy for this. The law component is an assessment of the strength and impartiality of the legal system, while the order component is an assessment of popular observance of the law. The advantage of the measure is that we have it available for all of our countries at a monthly frequency. We rescale the variable to be between 0 (worst) and 1 (best). Law and order proves a stronger differentiator of liquidity effects than does the level of liquidity itself. Countries with a high score for law and order have a coefficient on liquidity close to zero in the return regression, and return and liquidity shocks are not correlated at all. In contrast, the Amihud (2002) hypotheses are very significant for countries with a low score. The difference in coefficients is only statistically significant for the shocks correlations.

Finally, political risk in itself may help to segment markets. Institutional investors may face constraints on which countries they invest in depending on their political risk ratings. The final line considers the composite political risk rating from ICRG, rescaled to a (0,1) interval, as the interacting variable. The political risk rating provides the strongest results. In countries with little political risk, liquidity is not priced, whereas it is very strongly priced in countries with substantial political risk. The differences are strongly statistically significant.

3. Liquidity and Expected Asset Returns: A Simple Pricing Model

3.1 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:

$$\exp(r_{t+1}^{\text{net}}) = \frac{\exp(r_{t+1}^{\text{gross}})}{TC_{t+1}}, \tag{9}$$

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, L, that is:

$$\ell n(TC_{t+1}) = vL_{t+1} \ \ (v < 0), \tag{10}$$

where Equations (9) and (10) hold for each market, i, and for the United States, w. Recall that the liquidity measure, L, 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-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.[11] A zero daily return hopefully reflects 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 risk is priced. For liquidity risk 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 positively linked to liquidity risk, and shocks to liquidity affect 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.

3.2 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 ($L_{w,t+1}$). We assume that the log pricing kernel under market integration is given by:

$$m^I_{t+1} = \ell n(M^I_{t+1}) = -\gamma_w r^{\text{net}}_{w,t+1} - \gamma_{L,w} L_{w,t+1}, \tag{11}$$

where γ_w is the world price of market risk and $\gamma_{L,w}$ is the world price of liquidity risk. We do not offer a formal model justifying the presence of a liquidity term in the pricing kernel other than appealing to models with aggregate liquidity shocks correlated with preferences [e.g., Vayanos (2004)] or behavioral models where liquidity partially reflects the presence or absence of rational investors in the market [e.g., Baker and Stein (2004)]. It follows for all returns, $r^{net}_{i,t+1}$, that

$$E_t[exp(r^{net}_{i,t+1})M^I_{t+1}] = 1, \tag{12}$$

holds under global market integration.

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

[11] See Amihud and Mendelson (1986) for an interesting analysis of the resulting potential clientele effects, and Huang (2003) for an analysis of the effect of random holding horizons due to liquidity shocks on pricing.

distributed.[12] Then:

$$r_t^f = -E_t[m_{t+1}] - \tfrac{1}{2}\mathrm{Var}_{t[m_{t+1}]}. \tag{13}$$

Hence:

$$\begin{aligned} E_t[r_{i,t+1}^{\mathrm{net}}] = r_t^f &- \tfrac{1}{2}\mathrm{Var}_{t[r_{i,t+1}^{\mathrm{net}}]} + \gamma_w \mathrm{Cov}_{t[r_{i,t+1}^{\mathrm{net}}, r_{w,t+1}^{\mathrm{net}}]} \\ &+ \gamma_{L,w}\mathrm{Cov}_t[r_{i,t+1}^{\mathrm{net}}, L_{w,t+1}^{\mathrm{net}}]. \end{aligned} \tag{14}$$

Equation (14) follows from the main pricing Equation (12) and the normal distributional assumption, after substituting in Equation (13). 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 Equation (14) in terms of moments for gross returns:

$$\begin{aligned} \mathrm{Var}_t[r_{i,t+1}^{\mathrm{net}}] &= \mathrm{Var}_t[r_{t+1}^{\mathrm{gross}} - v_i L_{i,t+1}] \\ &= \mathrm{Var}_t[r_{i,t+1}^{\mathrm{gross}}] + v_i^2 \mathrm{Var}_t[L_{i,t+1}] - 2v_i \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, L_{i,t+1}], \end{aligned} \tag{15}$$

$$\begin{aligned} \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{net}}, r_{w,t+1}^{\mathrm{net}}] &= \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}} - v_i L_{i,t+1}, r_{w,t+1}^{\mathrm{gross}} - v_w L_{w,t+1}] \\ &= \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, r_{w,t+1}^{\mathrm{gross}}] + v_i v_w \mathrm{Cov}_t[L_{i,t+1}, L_{w,t+1}] \\ &\quad - v_i \mathrm{Cov}_t[L_{i,t+1}, r_{w,t+1}^{\mathrm{gross}}] - v_w \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, L_{w,t+1}], \end{aligned} \tag{16}$$

and

$$\mathrm{Cov}_t[r_{i,t+1}^{\mathrm{net}}, L_{w,t+1}] = \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, L_{w,t+1}] - v_i \mathrm{Cov}_t[L_{i,t+1}, L_{w,t+1}]. \tag{17}$$

Combining Equations (9), (10), and (14)–(17), we obtain:

$$\begin{aligned} &E_t[r_{i,t+1}^{\mathrm{gross}}] - r_t^f = \gamma_w \mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, r_{w,t+1}^{\mathrm{gross}}] \leftarrow \text{[world market risk]} \\ &+ (\gamma_{L,w} - \gamma_w v_w)\mathrm{Cov}_t[r_{i,t+1}^{\mathrm{gross}}, L_{w,t+1}] \leftarrow \text{[world liquidity risk]} \\ &+ v_i E_t[L_{i,t+1}] + v_i \mathrm{Cov}_t[L_{i,t+1}, r_{i,t+1}^{\mathrm{gross}}] \leftarrow \text{[local liquidity risk]} \\ &- v_i \gamma_w \mathrm{Cov}_t[L_{i,t+1}, r_{w,t+1}^{\mathrm{gross}}] \leftarrow \text{[cross liquidity-return effect]} \\ &+ (\gamma_w v_i v_w - \gamma_{L,w} v_i)\mathrm{Cov}_t[L_{i,t+1}, L_{w,t+1}] \leftarrow \text{[liquidity covariation effect]} \\ &- \tfrac{1}{2}\mathrm{Var}_{t[r_{i,t+1}^{\mathrm{gross}}]} - \tfrac{1}{2} v_i^2 \mathrm{Var}_{t[L_{i,t+1}]}. \leftarrow \text{[Jensen's inequality terms]} \end{aligned} \tag{18}$$

[12] Despite the statistical evidence against normality reported in Section 3, we nevertheless maintain the normality assumption for tractability and ease of interpretation of the resulting pricing equations. Moreover, the actual estimation uses a GMM approach and does not rely on normality.

The simple pricing relation in Equation (14) for net returns with two risks and a Jensen's inequality term turns into a pricing equation with eight terms. The pricing equation is similar but not identical to that implied by the model of Acharya and Pedersen (2005). First, Acharya and Pedersen's model is a pure transaction cost model so that $\gamma_{L,w} = 0$. Second, Acharya and Pedersen's model is formulated in simple returns and does not feature Jensen's inequality terms. It therefore has only five terms, as both the last line and the $\text{Cov}_t[r^{\text{gross}}_{i,t+1}, L_{i,t+1}]$ term represent Jensen's inequality effects [see Equation (15)].

The first term in Equation (18) reflects world market risk; the second term reflects world liquidity risk but the price of world liquidity risk is $\gamma_{L,w} - \gamma_w v_w$, not $\gamma_{L,w}$. 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: $v_i[E_t[L_{i,t+1}] + \text{Cov}_t[L_{i,t+1}, r^{\text{gross}}_{i,t+1}]]$. 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 is decreasing in the covariance between returns and local liquidity shocks. The latter seems counter intuitive, but arises because positive covariation increases the variance of net returns, which affects expected returns through Jensen's inequality (see Equation (15)).

The fourth line shows that a positive covariation between local liquidity and the market return implies a higher expected return. Acharya and Pedersen (2005) offer an extensive economic motivation for why investors may accept a lower return on a security that is liquid in a down market. Using data obtained from the Spanish stock market, Martinez et al. (2005) also find that higher liquidity-return covariances lead to higher expected returns. 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 et al. (2001a); Hasbrouck and Seppi (2000), and Huberman and Halka (2001). 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.

3.3 Pricing under market segmentation

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

$$m_{t+1}^{S} = \ell n(M_{t+1}^{S}) = -\gamma_i r_{i,t+1}^{\text{net}} - \gamma_{L,i} L_{i,t+1}. \tag{19}$$

Under joint normality:

$$E_t[r_{i,t+1}^{\text{net}}] = r_t^f - \tfrac{1}{2}\text{Var}_t[r_{i,t+1}^{\text{net}}] + \gamma_i \text{Var}_t[r_{i,t+1}^{\text{net}}] + \gamma_{L,i}\text{Cov}_t[r_{i,t+1}^{\text{net}}, L_{i,t+1}^{\text{net}}]. \tag{20}$$

Notice that r_t^f 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 parity holds, our expected excess return expressions are identical for local currency or dollar returns. Again, we must transform net into gross returns. We use:

$$\text{Cov}_t[r_{i,t+1}^{\text{net}}, L_{i,t+1}] = \text{Cov}_t[r_{i,t+1}^{\text{gross}}, L_{i,t+1}] - v_i \text{Var}_t[L_{i,t+1}] \tag{21}$$

and the expression for $\text{Var}_t[r_{i,t+1}^{\text{net}}]$ in Equation (15), to obtain:

$$\begin{aligned} E_t[r_{i,t+1}^{\text{gross}}] - r_t^f = {} & (\gamma_i - \tfrac{1}{2})\text{Var}_t[r_{i,t+1}^{\text{gross}}] \\ & + [\gamma_{L,i} - (\gamma_i - \tfrac{1}{2})2v_i]\text{Cov}_t[r_{i,t+1}^{\text{gross}}, L_{i,t+1}] \\ & + v_i E_t[L_{i,t+1}] + v_i[v_i(\gamma_i - \tfrac{1}{2}) - \gamma_{L,i}]\text{Var}_t[L_{i,t+1}]. \end{aligned} \tag{22}$$

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

3.4 Model parametrization

Because our models feature a number of country-specific parameters entailing a rather large parameter space, we model them as a time-invariant function of country-specific instruments, $z_{i,t}$. In the benchmark model, $z_{i,t} = Lib_{i,t}$. The transactions costs parameter is then modeled as:

$$v_i = v_I Lib_{i,t} + v_S(1 - Lib_{i,t}). \tag{23}$$

Hence, v_i depends only 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 $\gamma_{L,i} = \gamma_{L,S}$. We estimate three parsimonious models, which are all special cases of the following encompassing model:

$$\begin{aligned} E_t[r^{\text{gross}}_{i,t+1}] - r^f_t &= v_i E_t[L_{i,t+1}] + \theta^1_{i,t}\mathrm{Var}_t[r^{gross}_{i,t+1}] \\ &+ \theta^2_{i,t}\mathrm{Var}_t[L_{i,t+1}] + \theta^3_{i,t}\mathrm{Cov}_t[L_{i,t+1}, r^{gross}_{i,t+1}] \\ &+ \theta^4_{i,t}\mathrm{Cov}_t[L_{i,t+1}, r^{gross}_{w,t+1}] + \theta^5_{i,t}\mathrm{Cov}_t[L_{i,t+1}, L_{w,t+1}] \\ &+\theta^6_{i,t}\mathrm{Cov}_t[r^{gross}_{i,t+1}, L_{w,t+1}] + \theta^7_{i,t}\mathrm{Cov}_t[r^{gross}_{i,t+1}, r^{gross}_{w,t+1}] \end{aligned} \tag{24}$$

where $\theta^j_{i,t}$ is the parameter function for the j^{th} priced risk in country i:

$$\theta^j_{i,t} = \theta^j_S(1 - Lib_{i,t}) + \theta^j_I Lib_{i,t} \tag{25}$$

Two of the models we investigate impose the theoretical restrictions of complete integration or segmentation implied by the models derived in Sections 4.2 and 4.3. The third model mixes the two. In summary,

Parameter	Mixed model	Full integration	Full Segmentation
v_i	$v_I Lib_{i,t} + v_S(1 - Lib_{i,t})$	v_I	v_S
$\theta^1_{i,t}$	$(-\frac{1}{2})Lib_{i,t} + (\gamma_S - \frac{1}{2})(1 - Lib_{i,t})$	$-\frac{1}{2}$	$\gamma_S - \frac{1}{2}$
$\theta^2_{i,t}$	$(-\frac{1}{2})v_I^2 Lib_{i,t} + v_S[(\gamma_S - \frac{1}{2})v_S - \gamma_{L,S}](1 - Lib_{i,t})$	$-\frac{1}{2}v_I^2$	$v_S[v_S(\gamma_S - \frac{1}{2}) - \gamma_{L,S}]$
$\theta^3_{i,t}$	$v_I Lib_{i,t} + [\gamma_{L,S} - (\gamma_S - \frac{1}{2})2v_S](1 - Lib_{i,t})$	v_I	$\gamma_{L,S} - (\gamma_S - \frac{1}{2})2v_S$
$\theta^4_{i,t}$	$-v_I\gamma_w Lib_{i,t}$	$-v_I\gamma_w$	0
$\theta^5_{i,t}$	$(\gamma_w v_I - \gamma_{L,w})v_I Lib_{i,t}$	$(\gamma_w v_I - \gamma_{L,w})v_I$	0
$\theta^6_{i,t}$	$(\gamma_{L,w} - \gamma_w v_I)Lib_{i,t}$	$(\gamma_{L,w} - \gamma_w v_I)$	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 (including v_w) and the mixed model has seven parameters. The mixed model reduces to one of the extreme models when the financial openness indicator is either 0 or 1. We also investigate the relative role of the two channels through which liquidity can affect expected returns: transaction costs or systematic liquidity risk exposures. To focus on the first, we set $\gamma_{L,w} = \gamma_{L,S} = 0$; to focus on the latter, we set $v_w = v_i = 0$.

We also estimate VARs with alternative interaction variables: the level of liquidity, a law and order index, and a political risk index. We postulate that these variables may capture cross-country variation in the transaction costs or prices of risk. We therefore define:

$$v_{k,i} = v_{k,0} + v_{k,1} z_{i,t} \tag{26}$$

with $k = I, S$, and

$$\gamma_{S,i} = \gamma_{S,0} + \gamma_{S,1} z_{i,t} \tag{27}$$

$$\gamma_{L,S,i} = \gamma_{L,S,0} + \gamma_{L,S,1} z_{i,t}. \tag{28}$$

We expect that countries with lower liquidity levels, poorer law and order conditions, or higher political risks face greater prices of risk and transaction costs. Consequently, we anticipate $v_{k,1} > 0$, $\gamma_{S,1} < 0$, and $\gamma_{L,S,1} < 0$. We estimate these models under the same market integration hypotheses we explore and impose for the benchmark model: full integration, full segmentation, and a mixed model. Parameters in the table are replaced by the parameterizations in Equations (26)–(28). Ignoring v_w, the full integration (full segmentation) model now has 4 (6) parameters; the mixed model has 10.

We also consider an alternative mixed model. In this model, we view liquidity levels, political risk, or poor corporate governance proxied by the law and order variable as potential sources of market segmentation. This simply corresponds to replacing the $Lib_{i,t}$ variable under "mixed model" in the table by $z_{i,t}$. For example, when the political risk index equals 1 (meaning no political risk), the γ_i's are from the integrated model. When the index equals 0, the segmentation model applies, but the prices of risk do not vary directly with $z_{i,t}$.

3.5 Estimation

Before we can estimate the model, we must make auxiliary assumptions concerning 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:

$$\mathbf{u}_t = \left[\mathbf{u}_{i,t}, u_{w,t}, \mathbf{u}_{L_i,t}, u_{L_w,t}\right] \text{ for } i = 1, \ldots, N. \tag{29}$$

We assume that:

$$E[\mathbf{u}_t | \mathbf{I}_{t-1}] = 0. \tag{30}$$

This is a strong assumption, as it requires returns and the liquidity measure 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 obtain model residuals for use in a panel GMM estimation:

$$e_{w,t+1} = r_{w,t+1} - r_{f,t} - v_w L_{w,t+1} - \gamma_w u^2_{w,t+1} - \gamma_{L,w} u_{w,t+1} u_{L_w,t+1}$$

$$\begin{aligned} e_{i,t+1} = r_{i,t+1} - r_{f,t} - v_i L_{i,t+1} - \theta^1_{i,t} u^2_{i,t+1} - \theta^2_{i,t} u^2_{L_i,t+1} - \theta^3_{i,t} u_{L_i,t+1} u_{i,t+1} \\ -\theta^4_{i,t} u_{L_i,t+1} u_{w,t+1} - \theta^5_{i,t} u_{L_i,t+1} u_{L_w,t+1} \\ -\theta^6_{i,t} u_{i,t+1} u_{L_w,t+1} - \theta^7_{i,t} u_{i,t+1} u_{w,t+1}. \end{aligned}$$

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

$$\mathbf{g}_{t+1} = \begin{bmatrix} e_{w,t+1} \otimes \mathbf{x}_{w,t} \\ e_{i,t+1} \otimes (\mathbf{x}_{i,t}, z_{i,t}) \end{bmatrix}, \tag{31}$$

where we set $z_{i,t}$ equal to the interaction variables, including financial openness, employed in the VAR. In our empirical work, we primarily focus on the benchmark case, $\mathbf{x}_{i,t} = [r_{i,t}, L_{i,t}]$, corresponding to the bivariate VAR. For the emerging markets, the system has 72 orthogonality conditions for our baseline specification (with 18 extra for interaction analysis), where our least parsimonious model has only 10 parameters (the U.S. system has 3 additional conditions).

We use two specification tests. First, we report the standard test of over-identifying restrictions. Second, we compute a metric that weights 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 that is model-specific, this weighting scheme is constant across all models, and thus facilitates a comparison of our non-nested models. The metric is related to but not identical to the popular Hansen and Jagannathan (1991) distance metric, which measures the distance between the implied pricing kernel and the region of acceptable pricing kernels. The distance measure is given by:

$$\{E[g_{t+1}]' E[(R_{i,t+1} \otimes (\mathbf{x}_{i,t}, z_{i,t}))(R_{i,t+1} \otimes (\mathbf{x}_{i,t}, z_{i,t}))']^{-1} E[g_{t+1}]\}^{1/2}. \tag{32}$$

While it would be possible, building on results regarding the HJ distance measure, to derive the asymptotic distribution of the statistic [see Jagannathan and Wang (1996)], this distribution is likely to be a poor approximation to the true small sample distribution [see Kan and Zhou (2002); Ahn and Gadarowski (2004)]. Therefore, we simply use the distance measure as a statistic to compare models.

3.6 Empirical results

Our bivariate VARs, estimated above, deliver the *unexpected* return and liquidity shocks for each country used in the GMM estimation. It is important to note that the standard errors we will report ignore the sampling error associated with this first stage VAR and hence likely underestimate the true standard errors. We pre-estimate the U.S. parameters using a longer sample from 1962-2003 from CRSP. This ensures that the world parameters are estimated with maximal precision and are identical across models. It is difficult to identify both v_w and $\gamma_{L,w}$; therefore, we first consider a model where $v_w = 0$. The resulting model fits the data as well as the model with non-zero v_w and has positive prices of risk. The price of world market risk is 2.848 and significant. The price of world liquidity risk is 57.240, but imprecisely estimated. We will report an alternative model with $v_w \neq 0$ and $\gamma_{L,w} = 0$ as well.

3.6.1 Benchmark model. Table 8 (Panel A) presents the results for the three basic theoretical models associated with either a fully integrated case, a fully segmented case, or a mixed variant. Note that all models we consider are rejected with p-values below 0.01 based upon the tests of the 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. Given the limited time-series for emerging markets, however, inference could be different with more data.

To begin, we present the fully integrated case, for which we estimate only one new parameter, v_I—the gross-to-net return adjustment; γ_w—the pre-estimated price of world market risk, and $\gamma_{L,w}$—the pre-estimated price of world market liquidity risk are discussed above. The gross to net adjustment parameter is negative but not significantly different from zero. Evaluated at the average zero, this term represents about 4 basis points per month, a small but reasonable estimate. Of the models under consideration in Panel A, the fully integrated model has the largest distance statistic, 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 three parameters: v_S—the gross-to-net return adjustment,

γ_S—the price of local market risk, and $\gamma_{L,S}$—the price of local market liquidity risk. The v_S parameter is similar to v_I, and is also not significantly different from zero. The local price of market risk is not significant; however, the price of local liquidity risk is positive and significant. Of the main models considered, the fully segmented model is associated with the lowest distance metric. These estimates suggest a 53 and 27 basis points 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 financial openness proxy. In this case, the gross-to-net adjustment parameter is negative (but not significant) for fully segmented markets, but becomes an insignificant positive number for markets displaying greater foreign investor access. The price of local market risk is not significantly different from zero; however, the price of local liquidity risk is positive and highly significant. Nevertheless, the distance associated with the mixed model exceeds that of the full segmentation model. For segmented markets, these estimates suggest a -34 and 62 basis point per month compensation for local market and liquidity risk, respectively. For integrated markets, these estimates suggest a 44 and -31 basis point per month compensation for global market and liquidity risk, respectively (the latter due to a negative covariance).

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, $\gamma_{L,S}$ and $\gamma_{L,w}$ respectively. The removal of a transaction costs effect still yields a positive and significant price of local liquidity risk, but the price of market risk remains negative. The removal of all systematic liquidity pricing makes the local price of market risk positive, but it remains insignificantly different from zero. The v-parameters are now both negative. This model actually yields a distance metric that is quite close to that of the full segmentation model. We also report an alternative mixed model where the model for U.S. returns sets $\gamma_{L,w} = 0$, instead of $v_w = 0$. We find that v_w is -0.058 and marginally different from zero, but the price of world market risk is negative. The local prices of risk and transaction cost parameters are rather similar to the ones we estimated before, only that the price of local market liquidity risk is somewhat higher.

Finally, we also estimate the general mixed model, but we replace the value-weighted zero return liquidity measure with its equal-weighted counterpart. The pre-estimated U.S. pricing evidence is very similar to the equal-weighted liquidity case, but the price of world liquidity risk is now marginally significant. Here, the gross-to-net return transaction cost adjustment has the wrong sign and is not significant for segmented markets, but the price of local liquidity risk is large and strongly significant.

Table 8
Liquidity pricing 1993–2003

A. benchmark model	Full integration	Full segmentation	Mixed	Mixed (no transaction cost adjustment)	Mixed (no systematic liquidity)	Mixed (world transaction cost adjustment)	Mixed (equal-weighted liquidity)
v_S		−0.0008	−0.0095		−0.0098	−0.0043	0.0215
		(0.0030)	(0.0068)		(0.0055)	(0.0072)	(0.0079)
v_I	−0.0008		0.0051		−0.0014	−0.0013	−0.0003
	(0.0024)		(0.0031)		(0.0028)	(0.0031)	(0.0022)
γ_s		0.313	−0.203	−0.011	0.301	−0.431	−0.385
		(0.177)	(0.311)	(0.266)	(0.223)	(0.450)	(0.570)
$\gamma_{L,s}$		1.122	2.575	2.403		3.223	9.579
		(0.513)	(0.908)	(0.871)		(1.159)	(2.268)
v_w						−0.058	
						(0.029)	
γ_w	2.848		2.848	2.848	2.697	−0.805	2.292
	(1.100)		(1.100)	(1.100)	(1.124)	(1.948)	(1.106)
$\gamma_{L,w}$	57.240		57.240	57.240			35.910
	(41.080)		(41.080)	(41.080)			(18.450)
J-Test	282.7	188.9	183.5	194.8	214.4	191.7	179.8
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Correlation: ave. and pred. return	0.00	0.63	0.18	0.42	0.51	0.13	0.26
Distance metric	0.897	0.801	0.859	0.851	0.805	0.849	0.984

Table 8
(Continued)

B. Alternative model	High liquidity indicator				Political risk index				Law and order index			
	Full integration	Full segmentation	Mixed (delineate by financial openness)	Mixed (delineate by interaction variable)	Full integration	Full segmentation	Mixed (delineate by financial openness)	Mixed (delineate by interaction variable)	Full integration	Full segmentation	Mixed (delineate by financial openness)	Mixed (delineate by interaction variable)
υ_S		−0.0057 (0.0032)	−0.0078 (0.0079)	0.0119 (0.0065)		0.0074 (0.0204)	−0.2091 (0.0609)	−0.0045 (0.0182)		0.0112 (0.0076)	−0.0105 (0.0145)	0.0224 (0.0062)
$\upsilon_S{}^*$ Interaction		−0.0008 (0.0156)	−0.0464 (0.0351)			−0.0084 (0.0297)	0.3847 (0.1124)			−0.0175 (0.0106)	0.0658 (0.0507)	
υ_I	−0.0032 (0.0025)		0.0008 (0.0032)	−0.0116 (0.0093)	−0.0225 (0.0115)		0.0675 (0.0203)	0.0112 (0.0256)	0.0051 (0.0036)		0.0122 (0.0052)	−0.0347 (0.0086)
$\upsilon_I{}^*$ Interaction	−0.0426 (0.0101)		−0.0118 (0.0166)		0.0333 (0.0163)		−0.0970 (0.0284)		−0.0088 (0.0050)		−0.0210 (0.0086)	
γ_s		0.161 (0.205)	−0.391 (0.661)	0.326 (0.365)		0.228 (0.705)	−0.671 (1.481)	1.072 (0.548)		−0.213 (0.404)	0.038 (1.024)	0.709 (0.448)
$\gamma_s{}^*$ Interaction		0.656 (0.291)	2.008 (0.832)			−0.223 (1.288)	2.337 (2.767)			0.847 (0.672)	1.433 (1.925)	
$\gamma_{L,s}$		1.687 (0.470)	3.815 (1.428)	2.780 (1.339)		5.671 (3.452)	9.306 (7.134)	3.688 (1.422)		4.925 (2.131)	5.708 (3.663)	3.546 (1.432)

$\gamma_{L,s}{}^{*}$ Interaction		−5.523	−14.440			−6.110	−11.250			−5.298	−4.204	
		(1.525)	(4.664)			(5.734)	(13.980)			(3.525)	(9.648)	
γ_w	2.848		2.848	2.848	2.848		2.848	2.848	2.848		2.848	2.848
	(1.100)		(1.100)	(1.100)	(1.100)		(1.100)	(1.100)	(1.100)		(1.100)	(1.100)
$\gamma_{L,w}$	57.240		57.240	57.240	57.240		57.240	57.240	57.240		57.240	57.240
	(41.080)		(41.080)	(41.080)	(41.080)		(41.080)	(41.080)	(41.080)		(41.080)	(41.080)
J-Test	257.1	176.8	154.0	141.7	283.4	172.8	143.0	125.8	275.7	164.3	159.5	94.8
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Distance metric	0.962	0.842	0.896	0.892	0.896	0.854	0.981	0.766	0.919	0.836	0.933	0.682

This table presents evidence on liquidity pricing effects. Panel A contains evidence on our theoretical models: full integration, full segmentation, and mixed. The prices of world market and liquidity risk, γ_w and $\gamma_{L,w}$, are pre-estimated using GMM from the US CRSP data over the years 1962 to 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 openness 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 cost 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 value-weighted zero return liquidity measure with the equal-weighted counterpart. Panel B contains evidence on several alternative models for which the relevant local prices of risk differ across countries by interacting with three variables: a high liquidity level indicator, ICRG's political risk index, and ICRG's law and order index. For the ICRG indices, higher index values denote lower risk or higher quality. As in Panel A, we explore the following three models: full integration, full segmentation, and a mixed variant. We also consider a fourth model where the interacting variable determines the degree of market integration. In all cases, we report the standard test of over-identifying restrictions, and we also consider a comparison across models by evaluating distance metric similar to Hansen and Jagannathan (1991). Asymptotic standard errors are reported in parentheses.

Taken together, it is very clear that the various channels for risk compensation are extremely difficult to estimate with precision. However, the evidence on the price of local 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 distance measure criterion, but also generate the highest cross-sectional correlation between average returns over the sample with the expected returns generated by the various models. The best model here is the market segmentation (Panel A) model, for which the correlation between expected and average returns is 0.63, but the alternative that ignores liquidity risk also has a large correlation.

3.6.2 Alternative pricing models. Panel B of Table 8 reports the results for the models that use alternative instruments as interaction variables for the model parameters or as alternative "integration" indicators. For these models, we use the model residuals from the alternative VARs that we estimated using these instruments discussed in Section 2.4.4. The distance measures are therefore not strictly comparable to the ones in Panel A.

We start with the liquidity indicator. The fully integrated model yields the counterintuitive result that countries with better liquidity have a much larger (in absolute magnitude) transaction cost parameter than countries with low liquidity, whereas the transaction cost parameter is not significantly different from zero for low liquidity countries. The fully segmented model is again the best performing model in terms of the distance measure and the parameter estimates are reasonable. There is no significant difference between high and low transaction cost countries in terms of transaction cost parameters, but market (liquidity) risk is significantly more (less) priced in low transaction cost countries. The mixed model is indeed a mix of the fully integrated and segmented models, but its distance measure exceeds that of the fully segmented model. Finally, viewing the liquidity indicator as an effective openness indicator does not improve the performance of the model.

When the political risk indicator is used as an instrument, the transaction cost parameters for the fully integrated model are as expected: negative and significant for countries with high political risk, but positive or close to zero for countries with little political risk. Again, the fully segmented model performs better, but this time, two of the interaction effects are unexpected. The transaction cost parameter is only negative for countries with low political risk (although it is insignificant) and market risk is effectively not priced for these countries. However, local liquidity risk is not priced for these countries either. The mixed model appears over-parameterized with many insignificant coefficients and a distance measure that is much worse than the one for the segmented model. By far the best is the model where the political risk indicator is used as an effective market integration indicator. Here, countries with low political risk are assigned integrated world pricing and for such countries v_I is positive and not significantly different from zero. However, countries with high political risk follow a segmented pricing model with a negative but insignificant v_S parameter and significant local market and liquidity risks.

The models for the Law and Order Index behave similarly to these for the Political Risk Index. For both the segmented and integrated models, countries with a higher score on law and order have higher transaction cost parameters, which is counter-intuitive; however, the relative pricing of local market and liquidity risks in the fully segmented model makes sense: market (liquidity) risk is only important for countries with high (low) scores on the Law and Order Index. The mixed model again does not perform well, but using the Law and Order Index as an indicator of market integration yields by far the lowest distance measure. The only surprise is that v_I is negative and v_S is positive, both significantly so. This perhaps indicates that the model still needed to find a channel through which to price in local liquidity for the countries that score well on law and order, whereas the high and significant price of local liquidity risk suffices for the countries with low scores. In all, our results suggest that political risk and law and order may well be as important indicators of effective market integration as an openness index. Moreover, we find again consistent evidence of a positive price of local liquidity risk.

4. 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 et al. (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 use the measure in a panel VAR model for 18 emerging countries where we test the hypotheses for liquidity pricing put forward by Amihud (2002). We indeed find that the zero measure significantly predicts returns, and unexpected liquidity shocks are positively correlated with returns and negatively correlated with dividend yields.

Finally, we formulate and estimate a simple pricing model, which, apart from market risk, separates the transaction cost and systematic risk effects of liquidity variation on 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. Interestingly, when liquidity is priced, local factors matter even under the hypothesis of global market integration. We also find local systematic liquidity risk to be important empirically, much more so than local market risk. We also find that elevated political risk and poor law and order conditions may serve as effective segmentation indicators and there is a much larger role for liquidity in expected returns in countries with these properties.

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.

Appendix

Appendix Table
Monte Carlo analysis of return predictability

	Data Generating Process: no return predictability (null)	
	R_{t+1} on L_t for closed countries	
	Coefficient	t-statistic
Median	0.0009	0.03
Mean	−0.0009	−0.05
2.5%	−0.0576	−2.03
5.0%	−0.0493	−1.73
95.0%	0.0495	1.73
97.5%	0.0604	2.09

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 bivariate VAR(1) for returns and liquidity using our pooled MLE methodology. This table presents the mean and four relevant percentiles of the empirical distribution for the coefficients and robust t-statistics of excess returns on lagged liquidity.

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