# Liquidity and Expected Returns: Lessons from Emerging Markets

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**Abstract**

Given the cross-sectional and temporal variation in their liquidity, emerging equity markets provide an ideal setting to examine the impact of liquidity on expected returns. Our measure of liquidity is the proportion of zero daily firm returns, averaged over the month. We find that this liquidity measure 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 return shocks and negatively correlated with shocks to the dividend yield. Equity market liberalization significantly improves the level of liquidity, but has no significant effect on the relationship between liquidity and future returns. We consider a simple asset pricing model with liquidity and the market portfolio as risk factors, differentiating between integrated and segmented countries and periods. Models with local liquidity risks outperform all others models.

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# 1 Introduction

It is generally accepted 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. It follows that liquidity and trading costs may contribute to both the average equity premium in stocks and, if there is systematic variation in liquidity, to the time-variation in expected returns. For example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Datar, Naik and Radcliffe (1998), Chordia, Roll and Anshuman (2001), Chordia, Roll and Subrahmanyam (2002) all attempt to quantify the role of liquidity in U.S. expected stock returns. Jones (2002) finds that bid-ask spreads and turnover predict U.S. stock returns one period ahead using 100 years of annual data, whereas the decline in transaction costs may also have contributed to a fall of about 1% in the equity premium. Amihud (2002), using a 1964-1997 NYSE sample, finds that expected market illiquidity has a positive effect on ex ante excess returns, and unexpected illiquidity has a negative effect on contemporaneous stock returns. Furthermore, if liquidity varies systematically (see Chordia, Roll, and Subrahmanyam (2000) and Huberman and Halka (1993)), securities with returns positively correlated with market liquidity should have high expected returns (see Pastor and Stambaugh (2002) and Sadka (2002) for recent empirical work). Acharya and Pedersen (2002) develop a stylized model that leads to three different risk premia associated with changes in liquidity, and find these risk premia to be highly significant in U.S. data.[1]

Surprisingly, the growing body of research on liquidity primarily focuses on the United States, arguably the most liquid market in the world. In contrast, our research focuses on markets where liquidity effects may be particularly acute, namely emerging markets. In a 1992 survey by Chuhan, poor liquidity was mentioned as one of the main reasons that

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

prevented foreign institutional investors from investing in emerging markets. If the liquidity premium is an important feature of these data, the focus on emerging markets should yield particularly powerful tests and useful independent evidence. In addition, many emerging markets underwent a structural break during our sample that likely affected liquidity, namely equity market liberalization. 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 U.S. alone, the finding of expected return variation due to liquidity can always be ascribed to an omitted variable correlated with a liquidity proxy. After all, there are a priori reasons to suspect small liquidity effects in the U.S. The U.S. market is vast in the number of traded securities, and it has a very diversified ownership structure, combining long-horizon investors (less subject to liquidity risk) with short-term investors. Hence, we may observe clientele effects in portfolio choice that mitigate the pricing of liquidity. Such diversity in securities and ownership is lacking in emerging markets, making liquidity affects potentially more acute. 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 Bekaert and Harvey (2000) and Henry (2000).

Finally, we also contribute to the vast literature on return predictability. Jones (2002) finds that liquidity and transaction cost variables have more predictive power than dividend yields for U.S. stock returns, but a growing literature has found, somewhat surprisingly, dividend yields to be rather poor predictors of U.S. stock returns. Early work on emerging markets (see for example Harvey (1995) and Bekaert (1995)) found relatively strong predictability in emerging markets using standard predictive variables, including the dividend yield. Given the low correlation between emerging market and U.S. equity returns, our analysis provides interesting independent evidence regarding return predictability.

There are some serious obstacles to our analysis. First, the data in emerging markets are of relatively poor quality, and detailed transaction data (bid-ask spreads, for example) are not widely available. For example, Domowitz, Glen, and Madhavan (2001) explore trading costs and liquidity in an international context for many countries, but they are forced to focus on trade level data, provided by Elkins/McSherry Inc., over a two year period. Similarly, Jain (2002) explores the relation between equity market trading design and liquidity across various countries, but uses a hand collected time-series of bid-ask spreads spanning only several months. To examine the time-series patterns in liquidity, we construct a measure that relies on the incidence of observed zero daily returns in these markets. Lesmond, Ogden and Trzcinka (1999) argue that if the value of an information signal is insufficient to outweigh the costs associated with transacting, then market participants will elect not to trade, resulting in an observed zero return. The advantage of this measure is that it requires only a *time-series* of daily equity returns. Given the paucity of time-series data on preferred measures such as bid-ask spreads or bona-fide order flow (following Kyle (1985)), our measure is an attractive empirical alternative. Further, we demonstrate that this measure, the proportion of zero daily returns, is highly correlated with more traditional measures of transaction costs for emerging equity markets for the limited periods when overlapping data *are* available, and we compare its effects with the effects of turnover. Lesmond (2002) provides a more detailed analysis of emerging equity market trading costs, and confirms the usefulness of this measure. Second, even for this easily constructed measure, we still have relatively short time-series samples from the perspective of traditional asset pricing empirics, making pure time-series tests country-by-country less useful, especially given the volatility of emerging market returns. We therefore pool the data across emerging markets.

The remainder of the paper is organized as follows. Section 2 describes our data and characterizes our liquidity measures. Section 3 outlines a simple structural VAR model that we use to interpret the results. Section 4 details the econometric models we estimate. Section 5 reports various VAR estimates and evaluates the statistical robustness and significance of the results (using Monte Carlo analysis), as well as their economic significance. Section 6 provides preliminary evidence of liquidity pricing in emerging markets. Some concluding remarks are offered in the final section.

## 2 Liquidity Measures for Emerging Markets

### 2.1 *Data and Summary Statistics*

Our empirical evidence focuses on 19 emerging equity markets. From Standard and Poor's Emerging Markets Database, we collect monthly returns (U.S. dollar), in excess of the one-month Eurodollar rate, and dividend yields for the IFC Global Equity Market Indices. Summary statistics on the returns and dividend yields are presented in Table 1.

We also construct two measures of liquidity (or proxies for transaction costs) that will serve as the primary quantities of interest. First, following Amihud and Mendelson (1986), Atje and Jovanovic (1993), Bekaert and Harvey (1997), and Levine and Zervos (1998), we construct a measure of equity market turnover ($TURN$): 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. Table 1 provides some summary statistics. Zimbabwe exhibits the lowest level of average equity market turnover at 0.6% per month, whereas Taiwan exhibits the highest level at 21.6% per month. According to the World Bank's World Development Indicators, the average level of equity market turnover during this period for the United States is 6.5% per month, exceeding most, but not all, of the emerging markets presented in Table 1.

Second, given the paucity of realized transaction cost data for emerging equity markets, we employ a measure that reflects the effect of transactions costs directly on daily returns in these markets. Following Lesmond, Ogden and Trzcinka (1999) and Lesmond (2002), we construct the proportion of zero daily returns observed over the relevant month for each equity market. Daily returns data at the firm level 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 (see Table 1 for the number of firms employed for each country) listed on a domestic exchange. 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. The difference between the average and total reflects both increased Datastream coverage and actual equity issuance in these countries. For each country, we calculate the proportion of zero daily returns across all firms, and average this proportion over the month.

We present summary statistics for the proportion of zero daily returns measure in Table 1. As can be seen, this measure of liquidity/transactions cost is fairly persistent. Some of these equity markets exhibit a very large number of zero daily returns; Colombia, for example, has a 77% incidence of zero daily returns, on average, across domestically listed firms over the full period for which data are available, and the smallest incidence of zero daily returns is 11%, on average, in Taiwan. Given data limitations associated with the firm-level daily returns, we focus on subsamples of the data, for which the precise country inclusion criteria are detailed in Table 1. The first, which we will denote Sample I, contains 15 countries and covers January 1990 to May 2001. The second, which we will denote Sample II, contains 10 countries, and covers January 1988 to May 2001. The first two samples will form the basis of our formal empirical analysis in Section 3. Additionally, we will also explore the key relationships for an *unbalanced* panel (denoted Sample III) that includes all 19 countries from January 1987 to May 2001.

## 2.2 *Do zeros measure liquidity?*

Liquidity and transactions costs are notoriously difficult to measure [see O'Hara (2003) and Stoll (2000) for discussions]. The availability of detailed microstructural data in the U.S. market allows for the construction of sharper measures of liquidity. For example, Chordia, Roll and Subrahmanyam (2000, 2001, 2002) calculate daily measures of absolute and proportional bid-ask spreads, quoted share and dollar depth for 1988-1998. Unfortunately, such data are not generally available for emerging markets. Hence, we must rely on an indirect measure. Even for studies focusing on the U.S., indirect measures, starting with the seminal work of Roll (1984)[2], have been and remain popular.

There are a number of other possible liquidity measures. For example, Amihud (2002)

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

examines the average ratio of the daily absolute return to the dollar trading volume on that day. This ratio delivers the absolute (percentage) price change per dollar of daily volume. This is interpreted as the daily price impact of order flow. Pastor and Stambaugh (2002), construct a firm specific liquidity measure by regressing a firm's return minus the market return on the lagged firm return and the lagged signed dollar volume of trading using daily data. The greater the price reversal on the next day, the more negative the coefficient on signed dollar volume and the more illiquid is the stock. The regression is repeated every month for every firm. Each month, the coefficient on the signed volume is averaged to provide a market wide liquidity measure. The measure is adjusted for the time-trend in market capitalization. Their final liquidity measure is the innovation from a regression of changes in the market-wide liquidity measure on lagged changes and the lagged level. While these two measures are straightforward to apply, we do not have dollar volume data on a daily basis in emerging markets. Moreover, volume data are very challenging, 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 measure. First, information-less trades should not give rise to price changes in liquid markets. The market reaction to such a trade may also depend on the particular trading mechanism in place. Whereas trading mechanisms vary substantially across emerging markets, we do not think that liquidity trades dominate the behavior of our measure. Indirect evidence of this is the fact that the zero measure correlates negatively with turnover. The cross-sectional correlation between the average turnover and the average incidence of zero daily returns across our sample countries is $-0.52$, indicating that the transaction costs measure is potentially reflecting *relative* liquidity across the equity markets in our study. Table 2 presents correlations of these two liquidity measures *across time* within each country. On average, the correlation between the proportion of zero daily returns and equity market turnover within a country is $-0.38$.

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. However, Table 2 indicates that there is no consistent pattern in the correlation between estimates of conditional volatility and the liquidity measure.[3] The correlation is more often positive than negative, though economically small in most cases. On average, the correlation is effectively zero.

As an alternative, we also construct a measure of within-month volatility as in French, Schwert, and Stambaugh (1987). First, we sum the squared returns *at the firm level* within the month, and then average this sum across firms for that month. Table 2 presents correlations between the incidence of zeros and the within-month volatility across time for each country. On average, the average correlation between the proportion of zero daily returns and within-month volatility is $-0.23$. This is somewhat more pronounced than for the implied conditional volatility estimates above (certain countries exhibit a large degree of correlation), but still suggests that the proportion of zero measure is capturing a unique aspect of liquidity. Nevertheless, given the somewhat larger correlations between the incidence of zeros and both turnover and volatility, we also consider (but do not report) an alternative measure of liquidity that reflects the "residuals" from country-by-country projections of the proportion of zero returns on both turnover and within-month volatility. While these regressions yield R-squares typically between 0.25 and 0.40, the general predictability and asset pricing implications of using the "residual" rather than the liquidity level (as presented in the subsequent sections) are unaffected.

Third, it is possible that our measure artificially reflects other characteristics of the stock market. For example, markets with many small stocks may automatically show a higher level of non-trading compared to markets with larger stocks. Since these small stocks only represent a small part of the market, it is not clear how relevant the measure is as a market-

[3] Estimates of the conditional volatility are obtained by maximum likelihood for both symmetric GARCH(1,1) and asymmetric threshold GARCH(1,1) models of the measured monthly equity returns for each market. The TARCH model is developed by Zakoian (1990) and Glosten, Jaganathan, and Runkle (1993).

wide transactions cost measure. However, Table 1 reveals a negative relation between the number of companies used in the computation and the average proportion of daily zero returns, with the cross-sectional correlation being -0.50. A larger number of firms covered by Datastream seems to be associated with a lower incidence of zero returns.

Perhaps most convincing is to explore the relationship between the returns based measure of transaction costs and more standard measures. To this end, Table 2 also presents correlations with available bid-ask spreads. Bid-ask spread data for domestic firms are obtained from the mid to late 1990's for a few countries from the Datastream research files. We find that the proportion of daily zero returns measure is highly correlated, 67% on average, with the average 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 (2002) also documents that the proportion of zero daily returns is highly correlated with hand-collected bid-ask spreads for a broader collection of emerging equity markets. The correlation between equity market turnover and the bid-ask spread is only about -0.21, 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.

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

For the United States, we explore the relationship between the proportion of zero daily returns and three other measures of transaction costs/liquidity common in the literature. Hasbrouck (1999, 2003) constructs a Bayesian estimate of effective trading costs from daily data using a Gibbs-sampler version of the Roll model.[4] This methodology yields a posterior distribution for the Roll-implied trading costs from the first-order autocorrelation in returns. For US equity data, Hasbrouck (2003) shows that the correlations between the Gibbs estimate and estimates of trading costs based upon high frequency Trade and Quote (TAQ) data

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

are typically above 0.90 for individual securities in overlapping samples. Hasbrouck (2003) argues that Hasbrouck's (1999) effective cost and Amihud's (2002) price impact measures are, among standard transaction costs estimates based on daily data, most closely correlated with their high-frequency counterparts from TAQ data.

At the annual frequency from 1962-2001, we compare effective cost and price impact measures for the aggregate NYSE and AMEX markets with the incidence of zero daily returns in these markets. Shown in Fig. 1, the correlation between the proportion of zero daily returns and Hasbrouck's effective costs and Amihud's price impact are 0.42 and 0.40, respectively. All three series display a reduction (lower costs/higher liquidity) in the late 1960's, followed by an increase in the mid-1970's. The series again fall in the mid-1980's, with an increase in the early 1990's. Finally, the only major divergence in the series is exhibited in the last 5-years with a sharp drop in the incidence of zero returns at precisely the US exchange's move to 1/16th in 1997 and decimalization in 2000. The effective costs and price impact measures do not exhibit these declines. For comparison, we also plot the equally-weighted proportional bid-ask spreads on DJIA stocks from Jones (2001) in Fig. 1. Interestingly, unlike the other measures of transaction costs/liquidity, the proportional spread data do exhibit the sharp declines in the late 1990's in accordance with the reduced incidence of zero daily returns. The overall correlation between bid-ask spreads and the proportion of zeros is 30%. Taken together, this evidence suggests that the proportion of zero daily returns for the United States is, at the very least, associated with time-series variation in other measures of transaction costs and/or liquidity used in this literature.

We also compare the incidence of zero returns with the "reversal" measure suggested by Pastor and Stambaugh (2002) (PS). For the PS measure, we consider two alternative constructions. The first conducts firm-level regressions on daily data over each month, averages the reversal coefficients across all firms, and then averages within the year. The second method conducts the firm-level regression on daily data over each year, and averages the reversal coefficient across all firms. Unfortunately, these two measures show little correlation with one another and only the first method leads to correlations with Hasbrouck's (2003) effective costs, the Amihud (2002) price impact measure and bid-ask spreads that have the right sign. Unfortunately, the Pastor-Stambaugh measure, which measures liquidity, is positively correlated with the proportion of zero daily returns for both methods. Consequently, our measure fails to capture aspects of liquidity reflected in the reversal measure.[5]

## 2.4 *Equity market liberalization and liquidity*

First, we examine the relationship between both equity market turnover and the proportion of zero daily returns with equity market liberalization. In our empirical analysis, we scale the proportion of zero daily returns for each country by the average proportion of zero daily returns observed for all the firms in the Datastream research files for the United States, 0.154, over the full sample period. This number is comparable to that observed in a longer time-series of zero daily returns for the CRSP files presented in Lesmond, Ogden, and Trzcinka (1999).[6] The negative of this scaled quantity will hereafter represent our liquidity measure, $LIQ_t$; fewer observed zero returns may be associated with markets that exhibit lower transaction costs and greater liquidity.

Equity market liberalization takes place when a country first provides foreign investors access to the domestic equity market. Bekaert and Harvey (2000) report "Official Liberalization" dates which we employ to explore the nature of the relation between liquidity and financial liberalization. We construct an indicator of equity market liberalization that takes the value of one following liberalization and zero otherwise.

In Table 3, we present pooled time-series cross-sectional regressions of the two measures of liquidity on the lagged equity market liberalization indicator. Specifically, we regress either $LIQ$ or $TURN$ on the lagged equity market liberalization indicator, allowing for fixed effects (not reported), but cross-sectionally constraining the liberalization coefficient to be identical across countries. First, $LIQ$ increases significantly, on average, following

[5] 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 (second PS measure).

[6] The scaling not only expresses the liquidity measure relative to a meaningful benchmark, but also transforms the measure from a variable constrained to be in the $[0, 1]$ interval to a variable defined over the (positive) real line, which is useful for our subsequent empirical analysis.

equity market liberalization for Samples I, II, and III, suggesting a strong link between foreign investor access to the domestic equity market and liquidity. For example, over the 15 countries included in Sample I, the increase in $LIQ$ is consistent with an decline in the proportion of zero daily returns of about 11% [$0.71 \times 0.154$]. For the other samples, the decline is on the order of 5 to 6%. This decrease is economically significant given the average proportion of zero daily returns shown in Table 1 across our sample countries. Consistent with this conclusion, equity market turnover increases after an equity market liberalization. For Sample I, equity market turnover is about 0.8% higher per month, on average, for those countries that underwent an equity market liberalization. For the two other samples, the increase is somewhat smaller but still highly significant.

As an alternative to the 0/1 Official Liberalization indicator, Bekaert (1995) and Edison and Warnock (2003) propose a continuous measure of equity market "openness" designed to reflect the gradual nature of the increasing foreign "investability" of these markets. The measure is based on the ratio of the market capitalization of the constituent firms comprising the IFC Investable Index to those that comprise the IFC Global Index for each country. The IFC Global Index, subject to some exclusion restrictions, is designed to represent the overall market portfolio for each country, whereas the IFC Investable index is designed to better represent a portfolio of domestic equities that are available to foreign investors. Hence, a ratio of one means that all of the stocks are available to foreign investors. We run each pooled regression replacing the official liberalization indicator with the investability measure. Across the three samples considered, both $LIQ$ and equity market turnover significantly increase with greater foreign investor access. Aside from the $LIQ$ measure in Sample I, each effect is more pronounced with the gradual liberalization measure, corroborating the relationship between foreign access and local market liquidity. This evidence suggests that equity market liberalization is associated with significant improvements in liquidity and lower transaction costs.

Because a number of liberalizations occur in the early 1990s, it is conceivable that this result is not driven by the actual liberalizations but by a world-wide trend towards improved liquidity in the 1990s. Such a trend is very visible in the U.S. data. However, the liquidity measure overall shows very little correlation across emerging markets. The maximum bivariate correlation coefficient is 0.76, the minimum is -0.80, the median one is 0.08. It is very unlikely that a world-wide trend would drive the increases that we document.

# 3 Liquidity and Expected returns

## 3.1 *A simple econometric model*

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

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

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

We postulate that the log of the transaction cost measure is linearly related to the liquidity measure, $LIQ$, that is;

$$\ell n(TC_{t+1}) = vLIQ_{t+1} \ (v < 0) \tag{2}$$

Note that we implicitly assume that everybody has the same one-year or one-month horizon in which they trade once. Of course, in reality, the trading frequency is endogenous. It is likely that an asset with high transaction costs will be traded less frequently and held longer.[7] The total transaction cost associated with an asset could be measured as the turnover in a given year times the transaction cost, including fixed costs and the bid-ask spread (see Jones (2002)). Unfortunately, we cannot measure transaction costs that precisely since we do not have complete bid-ask spread data. Further, while these explicit costs of transacting in equity market are important, they do not reflect the implicit costs associated with trading, such as the price impact of trading. These additional costs may be particularly important in emerging equity markets. However, a zero daily return may reflect the presence of all

[7] See Amihud and Mendelson (1986) for an interesting analysis of the resulting potential clientele effects.

transaction costs market participants face. In our work, we consider both the proportion of zero daily returns and equity market turnover as imperfect indications of general liquidity and transaction costs in the markets under consideration.

Even under these simple assumptions, liquidity impacts expected returns, but it is a one for one effect and it need not lead to predictable variation in expected returns. Additionally, as a rapidly growing literature asserts (see, for example, Amihud (2001), Jones (2001), and Pastor and Stambaugh (2002)), liquidity is priced. For liquidity to be priced at the aggregate level, there must be a systematic component to liquidity variation, and overall, stocks must perform badly when liquidity dries up. In this case, the expected equity premium is negatively linked to liquidity, and shocks to liquidity change expected returns and hence prices. Analogous to the approach in Amihud (2001), we model this liquidity dependence as:

$$E_t[r_{t+1}^{\text{net}} - r_{f,t}] = \delta_0 + \delta_1 \cdot LIQ_t \tag{3}$$

where $r_t$ is the net log return and $r_{f,t}$ is the log risk free rate.

Expected return variation is completely driven by variation in liquidity, but the empirical model that we estimate also allows for other sources of predictable variation. An important hypothesis to test is whether $\delta_1 < 0$, which supports the hypothesis that liquidity is priced. If this is the case, return innovations will also be linked to liquidity innovations. In particular, define the unexpected net return as:

$$\epsilon_{t+1} = r_{t+1}^{\text{net}} - r_{f,t} - \delta_0 - \delta_1 \cdot LIQ_t \tag{4}$$

and unexpected liquidity shocks as:

$$\eta_{t+1} = LIQ_{t+1} - \alpha_0 - \alpha_1 \cdot LIQ_t. \tag{5}$$

That is, we assume liquidity follows a simple autoregressive process. Moreover, we write:

$$\epsilon_{t+1} = \omega\eta_{t+1} + \overline{\epsilon}_{t+1}, \tag{6}$$

with $\overline{\epsilon}_t$ the innovation to net returns unrelated to liquidity, and we expect $\omega > 0$.

Hence, the bivariate relation between measured gross returns and a liquidity measure can be written as:

$$r_{t+1}^{\text{gross}} = \bar{\delta}_0 + \bar{\delta}_1 LIQ_t + \bar{\omega}\eta_{t+1} + \bar{\epsilon}_{t+1} \tag{7}$$

where

$$\begin{aligned} \bar{\delta}_0 &= \delta_0 + \alpha_0 \cdot v \\ \bar{\delta}_1 &= \delta_1 + \alpha_1 \cdot v \\ \bar{\omega} &= \omega + v \end{aligned} \tag{8}$$

Measuring gross returns instead of net returns prevents the separate identification of $\delta_1$, $\omega$, and $v$, and hence a test of liquidity pricing: $\delta_1 < 0$ and $\omega > 0$ (see also Jones (2001)). Nevertheless, investigating the bivariate dynamics of returns and liquidity can be instructive. For example, because $v$ is negative, finding $\bar{\omega}$ to be greater than zero is sufficient to conclude that $\omega > 0$ and liquidity is likely priced. Likewise, the reduced form model for gross returns implied by equations (3)-(5) is an ARMA(1,1) process, where the first-order autocorrelation coefficient is a function of (but not identical to) $\alpha_1$. Hence, the model implies that some of the serial correlation in returns should disappear once the liquidity measure is introduced in the feedback equation. Therefore, our empirical specification should, at a minimum, include excess returns and the liquidity measure.

## 3.2 *The role of dividend yields*

Suppose dividends are stochastic but show little or no autoregressive dynamics. In this case, the dividend yield will primarily capture variation in discount rates, and under the null of the model in equations (3)-(5), liquidity will drive its time-variation. Dividend innovations directly impact returns but not dividend yields. Consequently, dividend yields should provide additional information on the pricing of liquidity. In particular, we expect the innovations in liquidity and dividend yields to be negatively correlated. On the other hand, if we include dividend yields as a predictive variable, it may well help capture the predictive power of liquidity, so it should decrease the magnitude of the coefficient on $LIQ$ in the return regression.

Alternatively, the dividend yield may capture other predictable components in returns. While dividend yields have long been viewed as particularly strong predictors of equity returns, some recent work (e.g. Ang and Bekaert (2003) and Goyal and Welch (2003)) demonstrates that this predictive power may not be statistically robust. Investigating the relative predictive power of the dividend yield and liquidity measures for emerging markets, which show very little correlation with established markets, is therefore interesting in its own right.

More generally, variation in the dividend yields can be viewed as a good proxy for variation in the cost of capital (e.g. Bekaert and Harvey (2000)). Hence, we estimate a multivariate VAR specification, including dividend yields, in addition to returns and $LIQ$. We also consider alternative VAR specifications, which include equity market turnover.

## 3.3 *A first look*

We examine the predictive relationship between excess returns and our liquidity measure, $LIQ$. In Table 4, we present pooled time-series cross-sectional regressions of excess returns on lagged liquidity, as well as regressions of excess returns on lagged equity market turnover and lagged dividend yields. In the pooled regressions, we allow for fixed country effects (not reported) and groupwise heteroskedasticity, but we cross-sectionally constrain the estimated predictability coefficient to be identical across countries.

First, across Samples I, II, and III, the estimated liquidity effects are both negative and significant. For example, in Sample I, the coefficient on lagged liquidity is more than two and a half standard errors from zero, suggesting a significant link between liquidity and future excess returns. For Sample III, which includes 19 emerging economies in an unbalanced panel, the estimated effect is more than 3.5 standard errors from zero, consistent with the effects observed in the smaller panels. When we regress returns on lagged returns, the serial correlation coefficient is small (around 0.10), but statistically different from zero. When adding the liquidity measure, this feedback coefficient on returns does not go to zero, suggesting that liquidity does not fully capture predictable autoregressive components in returns.

Equity market turnover does not predict excess returns for any of the samples we consider, indicating that the zero daily return based measure may be capturing an important component of market liquidity and transaction costs not captured by turnover. Importantly, the evidence on the predictive ability of the dividend yield across the three samples is mixed. For Samples I and II, the dividend yield effect is positive, but not statistically significant; however, for Sample III, including all 19 countries under consideration, the effect is significant. The mixed evidence is broadly consistent with the ambiguous relationships on predictability by the dividend yield documented across time-periods and markets (see Ang and Bekaert (2003), Engstrom (2002), and Goyal and Welch (2003)).

When we introduce the Official Liberalization indicator in the regression (both alone and interacted with the univariate predictor), the statistical significance of the liquidity effect is mostly lost.[8] The direct effect of liberalization on returns is, with one exception, negative but not always statistically significant, confirming the results in Bekaert and Harvey (2000) and Henry (2000). The dividend yield coefficients are on average larger post liberalization. Finally, the effect of liberalization on the predictive ability of the zero-measure is always positive, but its significance and economic magnitude is not robust across samples.

To explore the dynamic relationship between these variables more carefully, we propose a vector-autoregressive specification. We describe the pooled time-series cross-sectional VAR estimation next.

## 4 Econometric methods

We estimate the parameters describing the VAR process using a quasi-maximum likelihood (QMLE) methodology. We employ a normal log-likelihood function, and compute robust standard errors (see Bollerslev and Wooldridge (1992)). Let $\mathbf{x}_{i,t} = [r_{i,t}, LIQ_{i,t}]$, $[r_{i,t}, LIQ_{i,t}, dy_{i,t}]$, $[r_{i,t}, LIQ_{i,t}, TURN_{i,t}]$, or $[r_{i,t}, LIQ_{i,t}, TURN_{i,t}, dy_{i,t}]$. For country $i$, the base VAR(1) model is as follows:

$$\mathbf{x}_{i,t} = (\alpha_{0,i} + \alpha_1 * Lib_{i,t-1}) + \mathbf{A}\mathbf{x}_{i,t-1} + \Sigma_{i,t-1}^{1/2}\epsilon_{i,t} \tag{9}$$

[8] The effects using the investability measure of liberalization are similar and hence not reported.

where $\alpha_{0,i}$ denotes a vector of country-specific fixed effects for each endogenous variable; $\alpha_1$ denotes a vector of cross-sectionally restricted liberalization coefficients for each endogenous variable; and $\Sigma_{i,t}$, the VAR innovation conditional variance-covariance matrix for country $i$. $\Sigma_{i,t}$ is $\Sigma_{\text{before}}$ prior to a country's equity market liberalization and $\Sigma_{\text{after}}$ following a country's liberalization. $\Sigma_{\text{before}}$ and $\Sigma_{\text{after}}$ are restricted to be identical across countries and time. Finally, given the small time-series nature of our data sample, $\mathbf{A}$, the VAR matrix in companion form, is also restricted to be identical across countries. Given the insignificant results reported in Table 4, we do not allow for a liberalization interaction effect here. Hence, the parameters to be estimated are the country-specific fixed effects, $\alpha_{0,i}$; the liberalization effect, $\alpha_1$; the cross-sectionally restricted VAR matrix, $\mathbf{A}$; and the VAR innovation variance-covariance matrices before and after financial liberalization, $\Sigma_{\text{before}}$ and $\Sigma_{\text{after}}$.

We collect the relevant VAR innovations, $\epsilon_{i,t}$, from (9) for each country as follows:

$$\epsilon_t = \begin{bmatrix} \epsilon_{1,t} \\ \vdots \\ \epsilon_{N,t} \end{bmatrix}, \tag{10}$$

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:

$$\mathbf{\Omega}_t = \begin{bmatrix} \Sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \Sigma_{2,t} & \cdots & 0 \\ \vdots & & & \\ 0 & 0 & \cdots & \Sigma_{N,t} \end{bmatrix}. \tag{11}$$

Given the dimensionality issues, SUR effects are ignored across countries; that is, while VAR innovations are correlated within each country, innovations across countries are assumed uncorrelated. This construction is analogous to a *restricted* version of panel estimation with groupwise heteroscedasticity, with the country-specific VAR innovation variance-covariance matrix, $\Sigma_{i,t}$, depending only upon the liberalization indicator for that country.

The likelihood function for a single time period can be expressed as follows:

$$l_t = -\frac{k \cdot N}{2} \ln(2\pi) - \frac{1}{2} \ln |\mathbf{\Omega}_{t-1}| - \frac{1}{2} \epsilon_t' \mathbf{\Omega}_{t-1}^{-1} \epsilon_t \tag{12}$$

where $k$ is the number of endogenous variables, and $k \cdot N$ is the number of individual equations. Thus, the log-liklihood function for the full panel $(1, \ldots, T)$ is given by:

$$L = \sum_{t=1}^{T} l_t. \tag{13}$$

# 5 Empirical Results

## 5.1 *Quadravariate VAR: Returns, liquidity, turnover, and dividend yields*

In Table 5, we present estimation results for both Samples I and II for a quadravariate VAR(1), which includes excess returns, market liquidity, equity market turnover, and dividend yields in the set of endogenous variables. First, the excess returns display positive autocorrelation, on average across the countries, for both samples, consistent with Harvey (1995). For example, the coefficient on lagged returns is 0.094 for Sample I, almost four standard errors from zero. This coefficient is only slightly lower than the coefficient observed in the univariate regressions presented above.

Similar to the pooled regression presented above, the return coefficient on lagged liquidity is statistically significant, -0.012 (with a standard error of 0.004), for Sample I, but it is not statistically significant for Sample II, -0.007 (with a standard error of 0.005). If liquidity is indeed priced, then the resulting variation in the cost of capital will be incorporated into dividend yield variation. As a consequence, the inclusion of the dividend yield is likely to affect the estimated relations. We will contrast this finding to the case when dividend yields are excluded in the next section.

Interestingly, dividend yields do not significantly predict returns. Consistent with the pooled regressions presented above, for neither sample is the return coefficient on dividend yields statistically significant, and it is even negative for Sample I. There is also a strong relationship between liquidity and future dividend yields. The estimated coefficient is negative and statistically significant across both samples suggesting a liquidity effect on the cost of capital.

Lagged equity market turnover does not predict excess returns. While the signs are negative, which would suggest that increased equity market activity reduces the cost of capital, the effects are not statistically significant. Taken together, this evidence is consistent with the idea that the proportion of zero daily returns is picking up a feature of market liquidity and transaction costs not related to equity market turnover.

Next, we turn to the coefficient determining the relationship between liquidity and the lagged variables. First, lagged returns significantly affect future liquidity; the estimated coefficients are positive across both samples, and almost four standard errors from zero. High returns in one month predict improved subsequent market liquidity. Also, the liquidity variable displays significant autocorrelation; across both samples, the estimated coefficient on lagged liquidity is near 0.8. Acharya and Pedersen (2002), working with a liquidity measure proposed by Amihud (2002), find a persistence level of 0.942 for U.S. data. Dividend yields do predict liquidity: high dividend yields predict low liquidity, consistent with the dynamic relationship between returns and future liquidity.

Turnover, an alternative liquidity proxy, displays significant autocorrelation. Across both samples, the estimated coefficient on lagged turnover is also near 0.8. Further, high returns appear to be positively related to future turnover as they were with the liquidity measure. Surprisingly, increased market liquidity appears to be negatively related to future turnover, but the effect is only borderline significant.

The panels for the different variables also report the liberalization effect. For both samples, the lagged liberalization indicator does not significantly affect excess returns; this stands in contrast to the evidence presented in Bekaert and Harvey (2000), which suggests that some of the reduction in the cost of capital following liberalization that they document may in fact be due to the improved market liquidity that the liberalization facilitates. Consistent with the evidence documented in Bekaert and Harvey, dividend yields fall following equity market liberalization, but this effect is only statistically significant for Sample II. The dividend yield effect may be the result of improved liquidity, although the direct effect should be mostly controlled for through the lagged liquidity variable. Indeed, consistent with the pooled regressions presented above, equity market liberalization is associated with significantly improved market liquidity, and it increases turnover in both samples, but the effects are only significant for Sample I.

To explore the contemporaneous relationships between our four variables, Table 5 also displays the Cholesky decomposition of the VAR innovation variance-covariance matrix. Recall, the variance covariance matrix is allowed to differ across liberalization regimes. The off-diagonal component that effectively describes the average *within country* contemporaneous relationship between innovations in excess returns and liquidity, $c_{21}$, is positive for both samples considered across both liberalization regimes. The sign suggests that shocks to liquidity are positively correlated to returns shocks, which in conjunction with the significantly negative lagged liquidity coefficient, is consistent with the idea that liquidity is priced in the simple model presented in the previous section. It is unclear from the estimates whether the covariance significantly increases or decreases following equity market liberalization. However, for both samples the covariance is precisely estimated to be around 0.075 post-liberalization. In contrast, the standard deviation of both excess returns and the liquidity variable falls following equity market liberalization across both samples.

The contemporaneous covariances between liquidity and dividend yield shocks, $c_{42}$, is negative, consistent with the model that liquidity shocks are associated with a contemporaneous reduction in the cost of capital, but the estimates are borderline significant across the two samples only in the post-liberalization period. There also appears to be a positive contemporaneous relation between returns and turnover shocks, $c_{31}$, but the effect is not uniformly significant, and a strong positive relationship between liquidity and turnover shocks, $c_{32}$.

In sum, the quadravariate VAR suggests that the degree of equity market liquidity predicts future excess returns and that shocks to returns and liquidity are correlated. Next, we estimate alternative VAR specifications, with subsets of the four variables.

## 5.2 *Alternative VAR Specifications*

We provide results for both Samples I and II for three alternative VAR specifications. We estimate a bivariate VAR with excess returns and the liquidity measure; a trivariate VAR (A) with excess returns, liquidity, and equity market turnover; and a trivariate VAR (B) which excess returns, liquidity, and the dividend yield. In Table 6, we present evidence for these alternative specifications just for the liquidity pricing coefficients of interest. In particular, we present the predictive coefficients of lagged liquidity, turnover, and the dividend yield on excess returns for each specification, where appropriate. We also present estimates of certain elements of the Cholesky decomposition that describe the contemporaneous covariance between liquidity and return shocks. The other general effects are broadly unchanged from the quadravariate VAR specification presented in Table 5, and are not reported to conserve space.

First, for the bivariate specification, the lagged liquidity measure predicts excess returns across both samples considered, consistent with the pooled regression results presented in Table 4. The coefficients on lagged liquidity are -0.012 (standard error, 0.004) for Sample I and -0.009 (standard error, 0.004) for Sample II, indicating significant predictability. When we include equity market turnover (trivariate VAR A), market liquidity continues to significantly predict excess returns. The coefficients on lagged liquidity are slightly reduced, at -0.011 (standard error, 0.004) for Sample I and -0.009 (standard error, 0.004) for Sample II. Lagged equity market turnover does not predict excess returns. As in the full specification, while the estimate coefficients are negative, the effects are not statistically significant. Finally, when we consider the impact of the inclusion of the dividend yield without turnover (trivariate VAR B), the general effects are much like that presented above for the full quadravariate specification. The return coefficient on lagged liquidity is still statistically significant, -0.012 (standard error, 0.009), for Sample I; however, it is not significant for Sample II, -0.007 (standard error, 0.005). When the dividend yield is included, the reduction in the estimated predictability relationship is consistent with the model presented in the previous section. As above, we do not observe a significant relationship between dividend yields and future returns.

Table 6 also displays several components of the Cholesky decomposition of the VAR innovation variance-covariance matrix . The first estimate ($c_{21}$), associated with the contemporaneous covariance between return and liquidity shocks, is nearly identical to the estimates presented in Table 5 for the full specification. Because of the nature of the Cholesky decomposition, this is effectively true by construction since return projections typically have low time-series $R^2$'s. For the trivariate VAR that includes turnover, the estimated relationship between turnover and return shocks, $c_{31}$, is positive, but not significant across all samples and liberalization states. For the trivariate VAR that includes the dividend yield, the estimated relationship between dividend yield and return shocks ($c_{41}$) is negative, as one would expect. As above, the estimated relationship between liquidity and dividend yield shocks ($c_{42}$) is also still negative, but the effect is only significant in the post liberalization state.

Across the four VAR specifications considered, the negative relationship between market liquidity and future returns supports the idea that liquidity is priced. Further, the negative relation between liquidity and dividend yields corroborates this evidence. There does not appear to be a significant turnover or dividend yield effect on future returns. Note that in all estimations we control for the fact that equity market liberalization appears to significantly affect market liquidity, turnover, and dividend yields, at least for some of the samples considered.

## 5.3 *Statistical Significance and Robustness: A Monte Carlo Analysis*

The four VAR's lead to the following robust empirical results:

1) $LIQ$ negatively and significantly affects expected returns.

2) This effect is not driven out by the inclusion of dividends yields in the VAR, and the dividend yield does not significantly predict returns. It does, however, significantly predict $LIQ$.

3) Turnover does not drive out the $LIQ$ effect, although turnover and $LIQ$ are positively correlated.

4) The innovations to $LIQ$ and returns (dividend yields) are robustly positively (negatively) correlated, as would be expected when liquidity is priced.

Given well known small-sample biases in predictive regressions (see Stambaugh (1999) and Hodrick (1992)), we examine the small sample properties of the pooled time-series cross-sectional VAR estimates employed above in this section. For our largest cross-sectional sample, Sample I, of 15 countries, we conduct a Monte Carlo experiment to explore the small sample properties of our estimator and the observed liquidity effects. Given computational limitations, we focus only on the trivariate VAR, including returns, liquidity, and dividend yields. Let the simulated series be denoted as $\tilde{\mathbf{x}}_{i,t} = [r_{i,t}, LIQ_{i,t}, dy_{i,t}]$. The base VAR(1) model we simulate is as follows:

$$\tilde{\mathbf{x}}_{i,t} = (\alpha_{0,i} + \alpha_1 * Lib_{i,t-1}) + \mathbf{A}\tilde{\mathbf{x}}_{i,t-1} + \Sigma_{i,t-1}^{1/2}\tilde{\epsilon}_{i,t} \quad (14)$$

where $\tilde{\epsilon}_{i,t}$ is drawn from the standard normal distribution, $Lib_{i,t}$ represents the observed liberalization indicators, and the first row of $\mathbf{A}$ is constrained to be a row of zeros, so that under the null, lagged endogenous variables do not predict returns. However, the innovations of all variables are allowed to be correlated as in the observed data. For each replication, we estimate the unconstrained cross-sectionally restricted trivariate VAR(1) for returns, liquidity, and dividend yields using the pooled MLE methodology presented above.

Table 7 presents some relevant percentiles of the empirical distribution for the coefficients comprising the first row of $\mathbf{A}$, and for their corresponding $t$-statistics. First we focus on the relation between returns and the lagged liquidity variable. The median coefficient is -0.0002, and the median $t$-statistic is -0.04, indicating that estimation bias is not a serious issue for the observed liquidity effect. The $2.5^{th}$ percentile of the distribution shows a coefficient of -0.009, well above the estimated liquidity effect of -0.012 shown in Table 6, and the corresponding $t$-statistic is -2.08. The $t$-statistics are only slightly larger than what would be implied by a standard t-distribution; however, these critical values remain well below those obtained for the estimated liquidity effect in the trivariate VAR presented for Sample I in Table 6. It is unlikely that the small sample properties of the estimated standard errors for our other VAR specifications are qualitatively different from those presented here. In sum, the Monte Carlo evidence shows that the impact of market liquidity on future returns is not a statistical artifact.

Table 7 also presents some relevant percentiles for the coefficient describing the relationship between returns and the lagged dividend yields. The median coefficient is 1.18, and the median t-statistic is 0.509, indicating extreme estimation bias induced by the contemporaneous correlation between return and dividend yield shocks. The $97.5^{th}$ percentile of the distribution shows a coefficient of 5.99, and the corresponding t-statistic is 2.52. Confirming Ang and Bekaert (2002), this evidence suggests that extreme care must be taken when evaluating the importance of the dividend yield as a return predictor.

As a final check on the robustness of the results, we also conduct the bivariate VAR using a variant of the $LIQ$ measure, namely the (negative of the) log of the ratio of a country's zero measure relative to the U.S. average. This version smoothes liquidity outliers, and is defined on the real line. The results (not in tabular form) are nearly identical, with the projection coefficient of excess return on this lagged $LIQ$ measure equal to -0.025 (standard error, 0.007) and -0.020 (standard error, 0.007) for Sample I and II, respectively. Further, we observe the same positive contemporaneous correlation between the return and $LIQ$ shocks, suggesting the evidence on liquidity pricing presented above is robust.

We have identified a statistically significant effect of liquidity on (expected) returns. Is it also economically important? To explore this further, we consider a shock to the liquidity measure that brings it in line with the US level. Whereas the VAR dynamics are the same across countries, their initial liquidity levels differ relative to the US, so we can graph the shock response for each country. In Taiwan and Zimbabwe, for example, this liquidity shock would move the proportion of zero daily returns from 18% and 71%, respectively, to 15% (the US average). In Fig. 2, we plot the return response (from the bivariate VAR measured in monthly units) differentiating between the effects before and after official equity market liberalization. Because the effect is driven by the off-diagonal element, $c_{21}$, in the Cholesky decomposition of the innovation variance-covariance matrix, the effect is actually larger post-liberalization consistent with the reported estimates. The implied increase in realized returns for a positive liquidity shock of this magnitude varies from less than half a percent for Taiwan to almost 8% for Zimbabwe. Fig. 3 shows the effect of the shock on *expected* returns, again computed from the bivariate VAR. The implied decrease in expected returns for a positive liquidity shock of this magnitude varies from 0.2% for Taiwan to almost 4% for Zimbabwe.

## 6 The Price of Liquidity Risk

If liquidity is an aggregate risk and aggregate liquidity shocks are priced, a positive covariance with liquidity should carry a positive price of risk. That is, if a security's return is high when general liquidity increases, it should trade at a premium. In this section, we attempt to estimate the price of liquidity risk using the asset pricing framework of Campbell (1987) and Harvey (1989, 1991). They formulate a conditional version of the CAPM using a GMM framework in which expected returns are assumed to be linear functions of a set of instruments. In our case, we distinguish two priced risks, the market and liquidity. Moreover, we must distinguish between segmented and integrated capital markets and allow for the fact that we observe gross, not net, returns. Under segmentation, our model is:

$$r_{i,t} - r_{f,t} = v_0 LIQ_{i,t} + \gamma_i Var_{t-1}[r_{i,t}] + \gamma_{LIQ,i} Cov_{t-1}[r_{i,t}, LIQ_{i,t}] + e_{i,t} \tag{15}$$

The first term reflects the transformation from gross to net returns which we assume to be proportional to the liquidity measure for all countries. The second term is the traditional CAPM term ($\gamma_i$ is the local market price of risk). $\gamma_{LIQ,i}$ is the local price of liquidity risk. Under integration, the world market return and world market liquidity are priced risks. The model becomes:

$$r_{i,t} - r_{f,t} = v_1 LIQ_{i,t} + \gamma_w Cov_{t-1}[r_{i,t}, r_{w,t}] + \gamma_{LIQ,w} Cov_{t-1}[r_{i,t}, LIQ_{w,t}] + e_{i,t} \tag{16}$$

We still allow for a country specific translation from gross to net returns, but allow the proportionality constant to differ from the segmented case. Here, $\gamma_w$ represents the world price of market risk and $\gamma_{LIQ,w}$ is the world price of liquidity risk.

Our bivariate VAR on excess returns and liquidity acts as the first stage that defines *unexpected* returns and liquidity for each country. This is a strong assumption, as it requires returns and the liquidity measure to exhaust the information set (see Harvey (1991) for further discussion). To explore the pricing implications, we also estimate a comparable VAR for the U.S. market return and aggregate market liquidity. In practice, we construct the comparable proportion of zero daily returns series for the United States based upon the daily returns data obtained from the Datastream research files. As for each emerging market, we observe daily returns (using closing prices) for a large collection of firms that comprise the Datastream Total Market Index for the United States, and we calculate the proportion of each firm's daily returns, and average across all the firms listed; this is our measure of aggregate market liquidity. For consistency, our measure of the aggregate market return is the return on the U.S. Total Market Index from Datastream.

With the return and liquidity innovations (from the bivariate VAR) for each emerging economy and the aggregate market in the first step, we then estimate the following pricing moments in the second step using panel GMM:

$$\begin{aligned} e_{w,t} &= r_{w,t} - r_{f,t-1} - \alpha_{w,t} - \gamma_w \mathrm{Var}_{t-1}[r_{w,t}] - \gamma_{LIQ,w} \mathrm{Cov}_{t-1}[r_{w,t}, LIQ_{w,t}] \\ e_{i,t} &= r_{i,t} - r_{f,t-1} - \alpha_{i,t} - \gamma_w (Lib_{i,t}) \mathrm{Cov}_{t-1}[r_{i,t}, r_{w,t}] - \gamma_i (1 - Lib_{i,t}) \mathrm{Var}_{t-1}[r_{i,t}] \\ &- \gamma_{LIQ,w}(Lib_{i,t}) \mathrm{Cov}_{t-1}[r_{i,t}, LIQ_{w,t}] - \gamma_{LIQ,i}(1 - Lib_{i,t}) \mathrm{Cov}_{t-1}[r_{i,t}, LIQ_{i,t}] \end{aligned} \tag{17}$$

where $\alpha_{w,t} = v_1 \cdot LIQ_{w,t}$ and $\alpha_{i,t} = [v_1(Lib_{i,t}) + v_0(1 - Lib_{i,t})] \cdot LIQ_{i,t}$. In this system, we combine equations (15) and (16) using the liberalization indicators. This implicitly assumes that the liberalization constitutes a permanent, unanticipated break which is likely not entirely accurate in practice. For this reason, we also employ the investability index as an alternative liberalization indicator in the GMM estimation.[9]

The conditional variances and covariances follow from the relevant own- and cross-products of the bivariate VAR innovations $[\epsilon_{i,t},\ \epsilon_{w,t}]$ as in Harvey (1991). The second stage parameters to be estimated are $\{v_0, v_1, \gamma_w, \gamma_{LIQ,w}, \gamma_i, \gamma_{LIQ,i}\}$, which is a $2N + 4$ vector of parameters if each $\gamma_i$ and $\gamma_{LIQ,i}$ are assumed to be different across countries. The orthogonality conditions to estimate this system can be summarized as follows:

$$g_t = \begin{bmatrix} e_{w,t} \otimes x_{w,t-1} \\ e_{i,t} \otimes x_{i,t-1} \end{bmatrix} \tag{18}$$

with $x_{w,t-1} = [1, r_{w,t}, LIQ_{w,t}]$ and $x_{i,t-1} = [1, r_{i,t}, LIQ_{i,t}]$. This yields a total of (3+3$N$) orthogonality conditions, leaving $N - 1$ over-identifying restrictions.

[9]For simplicity, the innovations employed in the GMM pricing estimation are, in all cases, obtained from the bivariate VAR on returns and liquidity, including the official liberalization indicator as described in the previous section.

Table 8 presents the results on the pricing model. For all models, we fix the value of $\gamma_w$ at the value obtained in a univariate GMM estimation of the US return model (as specified above). It makes little sense that other countries should contaminate this estimate. The world price of market risk is estimated to be around 4.0, but has a relatively large standard error. Importantly, the standard errors reported in the table ignore the sampling error from the first stage VAR, and hence may underestimate the true standard error. We also constrain the local prices of risk to be identical across countries. In many ways, we view our estimation as exploratory.

Panel A contains the results for the main model. The first estimated model sets $v_0 = v_1 = 0$; that is, the net to gross return transformation is eliminated. This assumption ensures that no domestic variables enter the pricing equation for "liberalized" markets. The world price of liquidity risk has the expected positive sign, but is not significantly different from zero. However, when the intensity indicator is used instead of the official liberalization indicator, the sign switches. The sign of the local price of market risk is also not robust across specifications. Finally, the price of local liquidity risk is positive and generally significantly different from zero. Allowing $v_0$ and $v_1$ to differ from zero has no impact on these findings. In Sample II, the price of local liquidity risk now switches sign and becomes insignificantly negative, but the $v_0$ parameter is significantly negative.

To obtain more intuition on these results, Panels B through D report the estimation results for a number of alternative models. In Panel B, all countries are assumed to be fully integrated over the full sample (i.e. only world risks matter). The world price of liquidity risk continues to have the wrong sign. Allowing for $v_0$ does not change this result. In Panel C, we look at the other extreme case of full segmentation (i.e. only local risks matter). For this specification, the local prices of market risk have the wrong sign, but the price of liquidity risk has the right sign and is highly significant. So far, the only robust result seems to be that the price of local liquidity risk is an important driver of expected returns, and that this is likely true for both segmented and integrated countries. Therefore, Panel D considers a hybrid model that modifies our original model to have local liquidity risk enter pricing under both integration AND segmentation, but retains the feature that world risks matter only under integration. For all samples, the local price of liquidity risk is now positive and highly significant. Interestingly, for the official liberalization indicator, the world price of liquidity risk now also becomes positive. The other results remain unchanged. Hence, this evidence strongly suggests that local market liquidity is an important driver of expected returns in emerging markets, and that the liberalization process has not eliminated its impact.

In Table 9, we informally investigate the fit of the different asset pricing models using the implied pricing errors. To compute the latter, we first construct measures of the model-implied risk premia by multiplying the estimated risk prices in Table 8 by the time-series average of the associated cross-products (covariances) of the bivariate VAR innovations. To account for the gross to net adjustment, we take the time-series average of the liquidity level, $LIQ_i$, for each country. For each model, the average pricing error ($\alpha$) is then the difference between the observed average excess return and the model implied expected excess return. We compute cross-sectional $R^2$'s from the regression of the average excess return on the model predicted average excess returns. Of course, these regressions incorporate only 15 and 10 observations, so they should be viewed with caution.

Whereas the $\alpha' s$ are quite small on average, there are some large pricing errors, particularly in Sample II. The $R^2$'s confirm the message from the price of risk estimates: the $R^2$'s increase considerably when local liquidity risks are allowed to affect expected returns for all countries and time-periods. Moreover, the gross to net transformation generally does not contribute to the fit of the various models. We conclude that systematic variation in local liquidity is an important component of expected return variation for all emerging markets in our sample.

## 7 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 (2002) and Lesmond, Ogden and Trzcinka (1999): the proportion of daily zero firm returns averaged over the month. The measure is easy to compute and, as expected, is indeed positively correlated with bid-ask spreads (where available) and negatively correlated with equity market turnover. We find that the zero measure captures an aspect of liquidity that is not present in turnover. In all of our analysis, turnover has an insignificant impact on returns in the presence of the zero measure. We also show that the zero measure significantly predicts returns in emerging markets, and unexpected liquidity shocks are positively correlated with returns and negatively correlated with dividend yields. The predictive power of the zero measure generally survives in the presence of other instruments such as dividend yields.

Many of the markets we examine underwent a liberalization process. Importantly, liberalization may drive up liquidity, and affect the dynamic relation between returns and liquidity. Liberalization indeed significantly improves liquidity but has less of a robust effect on the relation between liquidity and future returns. Finally, if liquidity is priced, a two-factor model with market and liquidity risk may be a good description of expected returns. For emerging markets, there is the added complication that the market may be segmented or integrated. We consider models that allow for local or world market risk and local or global liquidity risk depending on whether a country is integrated or segmented. Whereas this analysis is exploratory in nature, we find a very clear dominant effect of local liquidity risks. In future work, we want to examine whether this result holds for developed markets as well or whether a world price of liquidity risk emerges.

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**Table 1**

## Summary Statistics

**Sample: 1987:01 2001:05**

*Excess Return (US$)*

| | ARG | BRA | CHL | COL | GRC | IND | IDO | JOR | KOR | MYS | MEX | PAK | PHL | PRT | TWN | THA | TUR | VEN | ZWE | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.031 | 0.019 | 0.014 | 0.010 | 0.015 | 0.003 | -0.006 | -0.001 | 0.004 | 0.003 | 0.019 | 0.002 | 0.004 | 0.007 | 0.013 | 0.004 | 0.025 | 0.013 | 0.012 | 0.010 |
| Standard Deviation | 0.220 | 0.174 | 0.079 | 0.094 | 0.120 | 0.094 | 0.145 | 0.042 | 0.125 | 0.106 | 0.125 | 0.097 | 0.110 | 0.140 | 0.140 | 0.127 | 0.202 | 0.137 | 0.112 | 0.126 |
| Autocorrelation | -0.077 | -0.020 | 0.224 | 0.405 | 0.084 | 0.110 | 0.191 | -0.034 | 0.014 | 0.102 | 0.270 | 0.081 | 0.262 | 0.289 | 0.050 | 0.118 | 0.091 | 0.037 | 0.190 | 0.126 |
| Observations | 173 | 173 | 173 | 173 | 173 | 173 | 137 | 173 | 173 | 173 | 173 | 173 | 173 | 148 | 173 | 173 | 173 | 173 | 173 | |
| **Sample Inclusion** | **I, II, III** | **I, III** | **I, III** | **III** | **I, II, III** | **I, III** | **I, III** | **III** | **I, II, III** | **I, II, III** | **I, II, III** | **III** | **I, II, III** | **III** | **I, II, III** | **I, II, III** | **I, II, III** | **I, III** | **I, II, III** | |

*Dividend Yield*

| | ARG | BRA | CHL | COL | GRC | IND | IDO | JOR | KOR | MYS | MEX | PAK | PHL | PRT | TWN | THA | TUR | VEN | ZWE | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.0021 | 0.0030 | 0.0038 | 0.0036 | 0.0034 | 0.0014 | 0.0011 | 0.0028 | 0.0012 | 0.0017 | 0.0016 | 0.0041 | 0.0010 | 0.0020 | 0.0007 | 0.0023 | 0.0032 | 0.0020 | 0.0043 | 0.0024 |
| Standard Deviation | 0.0012 | 0.0027 | 0.0019 | 0.0018 | 0.0019 | 0.0006 | 0.0007 | 0.0017 | 0.0006 | 0.0007 | 0.0006 | 0.0026 | 0.0005 | 0.0009 | 0.0003 | 0.0014 | 0.0019 | 0.0016 | 0.0022 | 0.0014 |
| Autocorrelation | 0.790 | 0.867 | 0.963 | 0.977 | 0.896 | 0.932 | 0.972 | 0.920 | 0.768 | 0.929 | 0.900 | 0.942 | 0.949 | 0.920 | 0.898 | 0.857 | 0.847 | 0.953 | 0.947 | 0.907 |
| Observations | 173 | 173 | 173 | 173 | 173 | 173 | 137 | 173 | 173 | 173 | 173 | 173 | 173 | 147 | 173 | 173 | 163 | 173 | 173 | |

*Turnover (Value Traded/MCAP)*

| | ARG | BRA | CHL | COL | GRC | IND | IDO | JOR | KOR | MYS | MEX | PAK | PHL | PRT | TWN | THA | TUR | VEN | ZWE | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.032 | 0.048 | 0.009 | 0.007 | 0.035 | 0.068 | 0.042 | 0.013 | 0.125 | 0.025 | 0.039 | 0.152 | 0.024 | 0.028 | 0.216 | 0.059 | 0.078 | 0.019 | 0.006 | 0.054 |
| Standard Deviation | 0.020 | 0.027 | 0.006 | 0.004 | 0.036 | 0.078 | 0.022 | 0.011 | 0.106 | 0.017 | 0.018 | 0.266 | 0.014 | 0.026 | 0.093 | 0.040 | 0.066 | 0.018 | 0.005 | 0.046 |
| Autocorrelation | 0.743 | 0.816 | 0.415 | 0.482 | 0.785 | 0.845 | 0.718 | 0.705 | 0.878 | 0.726 | 0.656 | 0.932 | 0.668 | 0.825 | 0.633 | 0.657 | 0.859 | 0.672 | 0.438 | 0.708 |
| Observations | 172 | 172 | 172 | 172 | 172 | 172 | 137 | 172 | 172 | 172 | 172 | 172 | 172 | 147 | 172 | 172 | 172 | 172 | 172 | |

*Zeros: Proportion of Daily Zeros in that month*

| | ARG | BRA | CHL | COL | GRC | IND | IDO | JOR | KOR | MYS | MEX | PAK | PHL | PRT | TWN | THA | TUR | VEN | ZWE | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.402 | 0.491 | 0.701 | 0.773 | 0.309 | 0.448 | 0.665 | 0.583 | 0.248 | 0.322 | 0.593 | 0.678 | 0.599 | 0.603 | 0.109 | 0.431 | 0.312 | 0.426 | 0.711 | 0.495 |
| Standard Deviation | 0.167 | 0.071 | 0.067 | 0.087 | 0.166 | 0.096 | 0.075 | 0.135 | 0.079 | 0.086 | 0.065 | 0.078 | 0.140 | 0.074 | 0.028 | 0.117 | 0.128 | 0.211 | 0.161 | 0.107 |
| Autocorrelation | 0.909 | 0.933 | 0.799 | 0.822 | 0.935 | 0.343 | 0.758 | 0.245 | 0.523 | 0.595 | 0.761 | 0.610 | 0.809 | 0.734 | 0.491 | 0.831 | 0.688 | 0.928 | 0.942 | 0.719 |
| Observations | 161 | 137 | 143 | 113 | 161 | 137 | 137 | 83 | 173 | 173 | 161 | 107 | 173 | 161 | 165 | 173 | 161 | 137 | 161 | |
| Ave. Number of Firms | 42.7 | 307.5 | 161.8 | 34.8 | 239.4 | 713.3 | 182.5 | 22.0 | 665.9 | 470.1 | 91.8 | 166.5 | 134.8 | 159.1 | 257.5 | 378.5 | 180.4 | 25.7 | 30.0 | |
| Total Number of Firms | 83 | 572 | 227 | 53 | 380 | 892 | 308 | 32 | 1612 | 815 | 163 | 240 | 217 | 271 | 562 | 401 | 295 | 53 | 89 | |

We collect monthly returns (U.S.$), in excess of the one-month Eurodollar rate, and dividend yields for the IFC Global Equity Market Indices from Standard and Poor's Emerging Markets Database. As a measure of equity market turnover, we also collect, for each month, the equity value traded for that month, divided by that month's equity market capitalization from Standard and Poor's. Finally, we construct the proportion of zero daily returns observed over the month for each equity market. Daily returns data at the firm level are obtained from the Datastream research files starting from the late 1980's. For each country, we observe daily returns (using closing prices) for a large collection of firms listed on a domestic exchange. For each country, we calculate the proportion of zero daily returns across all firms, and average this proportion over the month. Sample I includes 15 countries from 01/1990 to 05/2001; Sample II includes 10 countries from 01/1988 to 05/2001; and Sample III includes 19 countries from 01/1987 to 05/2001.

**Table 2**

## Correlations of Percentage of Zero Daily Returns with Alternative Measures of Liquidity

| | Bid-ask Spread | Turnover | Bid-ask Spread and Turnover | GARCH conditional volatility | TARCH conditional volatility | Within month Volatility |
|---|---|---|---|---|---|---|
| ARG | | -0.34 | | -0.43 | -0.32 | -0.54 |
| BRA | 0.36 | -0.36 | 0.18 | 0.69 | 0.74 | -0.09 |
| CHL | | -0.15 | | 0.02 | -0.32 | -0.35 |
| COL | | -0.14 | | -0.33 | -0.37 | -0.54 |
| GRC | | -0.58 | | 0.39 | 0.18 | -0.29 |
| IND | | -0.27 | | 0.37 | 0.15 | 0.14 |
| IDO | 0.69 | -0.34 | 0.17 | -0.19 | -0.14 | -0.30 |
| JOR | | -0.22 | | 0.05 | -0.01 | 0.18 |
| KOR | 0.73 | -0.39 | -0.54 | 0.07 | 0.15 | -0.24 |
| MYS | 0.60 | -0.67 | -0.39 | -0.13 | -0.11 | -0.37 |
| MEX | 0.84 | -0.48 | -0.48 | -0.21 | -0.21 | -0.21 |
| PAK | | -0.09 | | 0.20 | 0.00 | -0.12 |
| PHL | 0.81 | -0.54 | -0.18 | -0.25 | 0.15 | -0.19 |
| PRT | | -0.59 | | -0.06 | -0.14 | 0.04 |
| TWN | | -0.47 | | -0.31 | -0.30 | -0.59 |
| THA | | 0.00 | | 0.50 | 0.51 | 0.28 |
| TUR | | -0.64 | | 0.01 | 0.32 | -0.46 |
| VEN | | -0.43 | | 0.00 | 0.00 | -0.17 |
| ZWE | | -0.52 | | -0.29 | -0.27 | -0.47 |
| Average | 0.67 | -0.38 | -0.21 | 0.01 | 0.00 | -0.23 |

Bid-ask spreads at the firm level are obtained from the Datastream research files (where available) for the countries shown here. Estimates of conditional volatility are obtained for each country by maximum likelihood estimation of a symmetric GARCH(1,1) and an asymmetric TARCH(1,1). Following French, Schwert, and Stambaugh (1987), within-month volatility is constructed by first summing the squared returns *for each firm* within the month, and then averaging across firms for that month.

**Table 3**

## Liquidity and Equity Market Liberalization

| | ***Sample I: 1990:01 2001:05 15 countries (balanced)*** | | | ***Sample II: 1988:01 2001:05 10 countries (balanced)*** | | | ***Sample III: 1987:01 2001:05 19 countries (unbalanced)*** | | |
|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable | | Estimate | Standard error | | Estimate | Standard error | | Estimate | Standard error |
| *LIQ* | Liberalization Indicator | 0.7180 | *0.0386* | Liberalization Indicator | 0.3155 | *0.0412* | Liberalization Indicator | 0.3707 | *0.0333* |
| *TURN* | Liberalization Indicator | 0.0083 | *0.0003* | Liberalization Indicator | 0.0067 | *0.0002* | Liberalization Indicator | 0.0055 | *0.0002* |
| *LIQ* | Investability Indicator | 0.4060 | *0.0505* | Investability Indicator | 0.4081 | *0.0536* | Investability Indicator | 0.3837 | *0.0438* |
| *TURN* | Investability Indicator | 0.0329 | *0.0022* | Investability Indicator | 0.0279 | *0.0021* | Investability Indicator | 0.0211 | *0.0007* |

This table presents pooled regressions with fixed effects (not reported) of either the liquidity measure (*LIQ*) or equity market turnover (*TURN*) on either the Official Liberalization indicator or the investability measure of each market. In our empirical analysis, we scale the proportion of zero daily returns for each country by the average proportion of daily returns observed for all the firms in the Datastream research files for the United States, 0.154, over the full sample period; the negative of this value is *LIQ*. Samples I and II are balanced panels, whereas, Sample III employs all countries with available data in an unbalanced panel. We construct Newey-West (5) robust standard errors that also correct for groupwise heteroskedasticity.

**Table 4**

## Returns and Liquidity

| Dependent Variable: $R_{t+1}$ | *Sample I: 1990.01-2001.05 15 countries (balanced)* Estimate | Standard error | *Sample II: 1988.01-2001.05 10 countries (balanced)* Estimate | Standard error | *Sample III: 1987:01 2001:05 19 countries (unbalanced)* Estimate | Standard error |
|---|---|---|---|---|---|---|
| $LIQ_t$ | -0.0101 | *0.0040* | -0.0094 | *0.0038* | -0.0074 | *0.0021* |
| $R_t$ | 0.1043 | *0.0257* | 0.0927 | *0.0414* | 0.1235 | *0.0177* |
| $R_t$ | 0.1086 | *0.0256* | 0.1009 | *0.0410* | 0.1026 | *0.0191* |
| $LIQ_t$ | -0.0112 | *0.0039* | -0.0104 | *0.0038* | -0.0086 | *0.0025* |
| $LIQ_t$ | -0.0107 | *0.0079* | 0.0004 | *0.0058* | -0.0029 | *0.0043* |
| Liberalization $\text{Indicator}_t$ | 0.0069 | *0.0326* | -0.0448 | *0.0223* | -0.0274 | *0.0160* |
| $LIQ_t$*Lib $\text{Indicator}_t$ | -0.0001 | *0.0075* | -0.0137 | *0.0054* | -0.0052 | *0.0043* |
| $TURN_t$ | -0.0352 | *0.0495* | 0.0032 | *0.0565* | -0.0165 | *0.0244* |
| $TURN_t$ | -0.1805 | *0.1806* | 0.0505 | *0.1005* | 0.0749 | *0.0760* |
| Liberalization $\text{Indicator}_t$ | -0.0050 | *0.0097* | -0.0053 | *0.0103* | -0.0067 | *0.0046* |
| $TURN_t$*Lib $\text{Indicator}_t$ | 0.1527 | *0.1775* | -0.0532 | *0.0976* | -0.0911 | *0.0759* |
| $DY_t$ | 1.4812 | *2.9927* | 4.4140 | *2.5070* | 2.1560 | *1.1127* |
| $DY_t$ | 0.9645 | *5.1513* | -1.3094 | *3.4050* | 0.3583 | *1.4225* |
| Liberalization $\text{Indicator}_t$ | -0.0003 | *0.0169* | -0.0236 | *0.0136* | -0.0148 | *0.0071* |
| $DY_t$*Lib $\text{Indicator}_t$ | 1.0767 | *5.3225* | 8.8340 | *3.8662* | 2.9803 | *2.1072* |

Pooled regressions with fixed effects (not reported) of the return in excess of the one-month eurodollar rate on lagged returns, the liquidity measure, turnover, the dividend yield, and associated interactions with the Official Liberalization indicator. Samples I and II are balanced panels, whereas, Sample III employs all countries with available data in an unbalanced panel. We construct Newey-West (5) robust standard errors that also correct for groupwise heteroskedasticity.

**Table 5**

## Vector Autoregression

**Quadravariate: Returns, LIQ, Turnover and Dividend Yield**

| | Sample I | | Sample II | |
|---|---|---|---|---|
| **Dependent Variable: $R_{t+1}$** | Estimate | Standard error | Estimate | Standard error |
| $R_t$ | 0.094 | *0.022* | 0.079 | *0.025* |
| $LIQ_t$ | -0.012 | *0.004* | -0.007 | *0.005* |
| $TURN_t$ | -0.027 | *0.058* | -0.013 | *0.072* |
| $DY_t$ | -0.079 | *1.351* | 4.081 | *3.129* |
| Liberalization Indicator$_t$ | 0.015 | *0.012* | -0.001 | *0.014* |
| **Dependent Variable: $LIQ_{t+1}$** | | | | |
| $R_t$ | 0.265 | *0.077* | 0.320 | *0.084* |
| $LIQ_t$ | 0.776 | *0.015* | 0.794 | *0.016* |
| $TURN_t$ | -0.329 | *0.200* | -0.449 | *0.227* |
| $DY_t$ | -42.460 | *8.919* | -34.280 | *10.344* |
| Liberalization Indicator$_t$ | 0.092 | *0.046* | 0.070 | *0.035* |
| **Dependent Variable: $TURN_{t+1}$** | | | | |
| $R_t$ | 0.018 | *0.005* | 0.022 | *0.006* |
| $LIQ_t$ | -0.003 | *0.001* | -0.003 | *0.001* |
| $TURN_t$ | 0.784 | *0.014* | 0.761 | *0.017* |
| $DY_t$ | -1.065 | *0.571* | -2.215 | *0.777* |
| Liberalization Indicator$_t$ | 0.007 | *0.002* | 0.003 | *0.003* |
| **Dependent Variable: $DY_{t+1}$** | | | | |
| $R_t$ | **-0.055** | ***0.112*** | **-0.175** | ***0.104*** |
| $LIQ_t$ | **-0.036** | ***0.015*** | **-0.052** | ***0.019*** |
| $TURN_t$ | **-0.049** | ***0.200*** | **-0.321** | ***0.267*** |
| $DY_t$ | 0.899 | *0.009* | 0.852 | *0.009* |
| Liberalization Indicator$_t$ | **-0.044** | ***0.090*** | **-0.159** | ***0.058*** |
| **Cholesky Decomposition of VAR-COV matrix: Pre liberalization** | | | | |
| $c_{21}$ (Return and LIQ) | 0.035 | *0.043* | 0.111 | *0.030* |
| $c_{31}$ (Return and *TURN*) | 0.001 | *0.002* | 0.004 | *0.002* |
| $c_{41}$ (Return and dy) | **-0.678** | ***0.102*** | **-0.145** | ***0.055*** |
| $c_{42}$ (LIQ and dy) | **-0.135** | ***0.094*** | **-0.091** | ***0.055*** |
| **Cholesky Decomposition of VAR-COV matrix: Post liberalization** | | | | |
| $c_{21}$ (Return and LIQ) | 0.077 | *0.010* | 0.076 | *0.012* |
| $c_{31}$ (Return and *TURN*) | 0.007 | *0.001* | 0.009 | *0.001* |
| $c_{41}$ (Return and dy) | **-0.191** | ***0.009*** | **-0.207** | ***0.014*** |
| $c_{42}$ (LIQ and dy) | **-0.023** | ***0.009*** | **-0.027** | ***0.013*** |

This table presents quadravariate VAR maximum likelihood estimates, including excess return, *LIQ*, turnover, and the dividend yield as endogenous variables. The lagged Official Liberalization indicator is included as an additional exogenous variable. Further, the VAR innovation variance-covariance matrix, for which the 4-elements of the Cholesky decomposition are presented, is assumed to differ across liberalization state. We also present Bollerslev and Wooldridge (1992) robust standard errors. Estimates (and associated standard errors) in **bold** are multiplied by 1000.

**Table 6**

## Alternative VAR Specifications

| Dependent Variable: $R_{t+1}$ | Bivariate | | Trivariate A | | Trivariate B | | Quadravariate | |
|---|---|---|---|---|---|---|---|---|
| | Sample I | Sample II | Sample I | Sample II | Sample I | Sample II | Sample I | Sample II |
| *LIQ* $_t$ | -0.012 | -0.009 | -0.011 | -0.009 | -0.012 | -0.007 | -0.012 | -0.007 |
| | *0.004* | *0.004* | *0.004* | *0.004* | *0.004* | *0.005* | *0.004* | *0.005* |
| *TURN* $_t$ | | | -0.028 | -0.025 | | | -0.027 | *0.072* |
| | | | *0.058* | *0.066* | | | *0.058* | *0.066* |
| $DY_t$ | | | | | -0.210 | 3.746 | -0.079 | 4.081 |
| | | | | | *2.663* | *3.117* | *1.351* | *3.129* |
| **Cholesky Decomposition of VAR-COV matrix: Pre liberalization** | | | | | | | | |
| $c_{21}$ (Return and LIQ) | 0.034 | 0.114 | 0.033 | 0.114 | 0.036 | 0.111 | 0.035 | 0.111 |
| | *0.043* | *0.030* | *0.043* | *0.030* | *0.043* | *0.030* | *0.043* | *0.030* |
| $c_{31}$ (Return and *TURN* ) | | | 0.001 | 0.004 | | | 0.001 | 0.004 |
| | | | 0.002 | *0.002* | | | *0.002* | *0.002* |
| $c_{41}$ (Return and dy) | | | | | **-0.677** | **-0.144** | **-0.678** | **-0.145** |
| | | | | | ***0.102*** | ***0.055*** | ***0.102*** | ***0.055*** |
| $c_{42}$ (LIQ and dy) | | | | | **-0.135** | **-0.091** | **-0.135** | **-0.091** |
| | | | | | ***0.094*** | ***0.055*** | ***0.094*** | ***0.055*** |
| **Cholesky Decomposition of VAR-COV matrix: Post liberalization** | | | | | | | | |
| $c_{21}$ (Return and LIQ) | 0.077 | 0.075 | 0.077 | 0.075 | 0.077 | 0.076 | 0.077 | 0.076 |
| | *0.010* | *0.012* | *0.010* | *0.012* | *0.010* | *0.012* | *0.010* | *0.012* |
| $c_{31}$ (Return and *TURN* ) | | | 0.007 | 0.009 | | | 0.007 | 0.009 |
| | | | *0.001* | *0.001* | | | *0.001* | *0.001* |
| $c_{41}$ (Return and dy) | | | | | **-0.190** | **-0.207** | **-0.191** | **-0.207** |
| | | | | | ***0.009*** | ***0.014*** | ***0.009*** | ***0.014*** |
| $c_{42}$ (LIQ and dy) | | | | | **-0.023** | **-0.026** | **-0.023** | **-0.027** |
| | | | | | ***0.009*** | ***0.013*** | ***0.009*** | ***0.013*** |

This table presents maximum likelihood estimates for three alternative VAR specifications: a bivariate VAR including excess returns and LIQ; a trivariate VAR (A) including excess return, LIQ, and turnover; and a trivariate VAR (B) including excess returns, LIQ, and the dividend yield, as well as the quadravariate estimates presented in Table 5. As in Table 5, the Official Liberalization indicator is included in all cases as an additional exogenous variable. To conserve space, we only present the predictive coefficients of LIQ, turnover, and dividend yields on future excess returns. We also present the off-diagonal element of the Cholesky decomposition associated with the contemporaneous covariances between returns, LIQ, turnover, and dividend yields (plus dividend yields with LIQ), which are assumed to differ across liberalization state. We also present Bollerslev and Wooldridge robust standard errors below each estimate in italics. Estimates (and associated standard errors) in bold are multiplied by 1000.

**Table 7**

# Monte Carlo Analysis of Return Predictability

| | $R_{t+1}$ on $LIQ_t$ | | $R_{t+1}$ on $DY_t$ | |
|---|---|---|---|---|
| | Coefficient | T-statistic | Coefficient | T-statistic |
| Median | -0.0002 | -0.04 | 1.18 | 0.51 |
| Mean | -0.0003 | -0.06 | 1.24 | 0.53 |
| 2.5% | -0.0089 | -2.08 | -3.17 | -1.46 |
| 97.5% | 0.0078 | 1.88 | 5.99 | 2.52 |

For Sample I (15 countries), we simulate from the estimated trivariate VAR, including returns, liquidity, and dividend yields, except that under the null, returns are not predictable by lagged endogenous variables. However, the innovations of all variables are allowed to be correlated as in the observed data. We employ the observed liberalization indicators for each replication. For each replication, we then estimate the unconstrained cross-sectionally restricted trivariate VAR(1) for returns, liquidity, and dividend yields using the pooled MLE methodology presented above. This table presents the mean and three relevant percentiles of the empirical distribution for the coefficients and robust *t*-statistics of excess returns on lagged *LIQ* and the dividend yield.

**Table 8**

# Liquidity Pricing

## Panel A: Segmentation/Integration Model

*With Official Liberalization Indicator*

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.397 | 0.375 | 0.003 | 0.313 |
| $\gamma_{liq,w}$ | 0.164 | 0.291 | 0.284 | 0.578 |
| $\gamma_{liq,i}$ | 1.251 | 0.452 | 0.086 | 0.448 |
| | | | | |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.688 | 0.442 | 0.248 | 0.351 |
| $\gamma_{liq,w}$ | 0.178 | 0.295 | 1.061 | 0.596 |
| $\gamma_{liq,i}$ | 0.850 | 0.445 | -0.355 | 0.503 |
| $v_0$ | -0.0057 | 0.0025 | -0.0057 | 0.0022 |
| $v_1$ | 0.0000 | 0.0006 | -0.0020 | 0.0016 |

*With Intensity Indicator*

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.554 | 0.264 | 0.430 | 0.336 |
| $\gamma_{liq,w}$ | -0.472 | 0.420 | -0.547 | 0.523 |
| $\gamma_{liq,i}$ | 1.292 | 0.244 | 0.927 | 0.329 |
| | | | | |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.575 | 0.367 | 0.435 | 0.416 |
| $\gamma_{liq,w}$ | -0.494 | 0.447 | -0.858 | 0.530 |
| $\gamma_{liq,i}$ | 1.299 | 0.245 | 0.893 | 0.377 |
| $v_0$ | -0.0004 | 0.0015 | 0.0000 | 0.0017 |
| $v_1$ | -0.0001 | 0.0006 | 0.0015 | 0.0017 |

**Panel B: Full Integration Model**

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_{liq,w}$ | -0.157 | 0.292 | -0.834 | 0.387 |
| | | | | |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_{liq,w}$ | -0.129 | 0.293 | -0.507 | 0.412 |
| $v$ | -0.0004 | 0.0005 | -0.0010 | 0.0010 |

**Panel C: Full Segmentation Model**

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_i$ | -0.203 | 0.121 | -0.153 | 0.129 |
| $\gamma_{liq,i}$ | 0.985 | 0.122 | 0.661 | 0.175 |
| | | | | |
| $\gamma_i$ | -0.190 | 0.124 | -0.207 | 0.125 |
| $\gamma_{liq,i}$ | 0.985 | 0.123 | 0.592 | 0.175 |
| $v$ | -0.0001 | 0.0005 | -0.0016 | 0.0009 |

**Panel D: Modified Segmentation/Integration Model**

*With Official Liberalization Indicator*

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.447 | 0.125 | -0.189 | 0.132 |
| $\gamma_{liq,w}$ | 0.764 | 0.286 | 1.182 | 0.535 |
| $\gamma_{liq,i}$ | 1.020 | 0.119 | 0.629 | 0.188 |
| | | | | |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.343 | 0.124 | -0.210 | 0.137 |
| $\gamma_{liq,w}$ | 0.515 | 0.295 | 1.484 | 0.587 |
| $\gamma_{liq,i}$ | 1.073 | 0.123 | 0.587 | 0.193 |
| $v_0$ | -0.0037 | 0.0015 | -0.0039 | 0.0023 |
| $v_1$ | 0.0016 | 0.0006 | -0.0008 | 0.0014 |

*With Intensity Indicator*

| | Sample I | | Sample II | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.424 | 0.123 | -0.161 | 0.103 |
| $\gamma_{liq,w}$ | 0.052 | 0.355 | -0.898 | 0.575 |
| $\gamma_{liq,i}$ | 1.014 | 0.117 | 0.602 | 0.173 |
| | | | | |
| $\gamma_w^*$ | 4.140 | 2.053 | 3.885 | 1.948 |
| $\gamma_i$ | -0.324 | 0.126 | -0.055 | 0.129 |
| $\gamma_{liq,w}$ | -0.250 | 0.409 | -1.914 | 0.641 |
| $\gamma_{liq,i}$ | 1.064 | 0.125 | 0.609 | 0.198 |
| $v_0$ | -0.0004 | 0.0011 | -0.0022 | 0.0012 |
| $v_1$ | 0.0018 | 0.0006 | 0.0043 | 0.0015 |

The * indicates that the price of world market risk $\gamma_{w,}$ is estimated using GMM from the US data alone over the corresponding sample period. In Panel A, world market and liquidity factors are priced only under integration, whereas local market and liquidity risks are priced under segmentation. In Panel B, only world market and liquidity factors are priced at all times; in Panel C, only local market and liquidity factors are priced at all times. In Panel D, the world market and liquidity factors are priced only under integration, whereas local market and liquidity risks are priced at all times. We estimate each model using both the official liberalization and the investability indicators to measure financial integration. We estimate each model with and without a local liquidity adjustment cost, v. Robust standard errors are computed using Newey West (1987) with 5 lags.

Table 9

## Liquidity Pricing in the Cross-section

| Model | Sample I: 1990.01-2001.05 15 countries | | | | Sample II: 1988:01 2001:05 10 countries | | | |
|---|---|---|---|---|---|---|---|---|
| | | $\alpha_i$ | | | | $\alpha_i$ | | |
| | R-square | Average | Maximum | Minimum | R-square | Average | Maximum | Minimum |
| **Official Liberalization** | | | | | | | | |
| **Segmentation/Integration** | 0.00 | 0.000 | 0.019 | -0.017 | 0.13 | 0.005 | 0.024 | -0.007 |
| **Segmentation/Integration (with net)** | 0.01 | -0.001 | 0.019 | -0.017 | 0.00 | 0.000 | 0.022 | -0.011 |
| **Investability** | | | | | | | | |
| **Segmentation/Integration** | 0.02 | 0.000 | 0.017 | -0.015 | 0.02 | -0.001 | 0.022 | -0.013 |
| **Segmentation/Integration (with net)** | 0.05 | -0.002 | 0.014 | -0.018 | 0.16 | 0.001 | 0.025 | -0.012 |
| **Full Integration** | 0.06 | -0.001 | 0.018 | -0.017 | 0.13 | 0.002 | 0.025 | -0.010 |
| **Full Integration (with net)** | 0.05 | -0.002 | 0.017 | -0.018 | 0.10 | 0.000 | 0.024 | -0.012 |
| **Full Segmentation** | 0.29 | 0.000 | 0.015 | -0.012 | 0.57 | 0.005 | 0.018 | -0.004 |
| **Full Segmentation (with net)** | 0.29 | -0.001 | 0.014 | -0.013 | 0.33 | 0.003 | 0.019 | -0.007 |
| **Official Liberalization** | | | | | | | | |
| **Mod Segmentation/Integration** | 0.07 | -0.001 | 0.013 | -0.019 | 0.44 | 0.004 | 0.017 | -0.008 |
| **Mod Segmentation/Integration (with net)** | 0.16 | -0.001 | 0.012 | -0.015 | 0.24 | 0.002 | 0.017 | -0.009 |
| **Investability** | | | | | | | | |
| **Mod Segmentation/Integration** | 0.26 | -0.001 | 0.013 | -0.015 | 0.43 | 0.001 | 0.014 | -0.010 |
| **Mod Segmentation/Integration (with net)** | 0.19 | -0.001 | 0.014 | -0.014 | 0.10 | 0.001 | 0.017 | -0.010 |

This table presents evidence on the cross-sectional pricing errors associated with each model presented in Table 8. We construct measures of the model implied expected excess returns by multiplying the risk prices in Table 8 by the average of the relevant cross-products of the bivariate VAR innovations. To account for the gross to net adjustment, we also take the average of LIQ for each country. The column labeled "R-square" is the r-squared from the cross-sectional regression of the observed average excess return for each country on the model implied expected excess return. For each model, we also construct ``alphas" by measuring the difference between the observed average and the model implied excess returns; some summary statistics on the alphas are provided. The alphas are in monthly units.

Figure 1

Comparison of Transaction Costs/Liquidity Measures using US Data

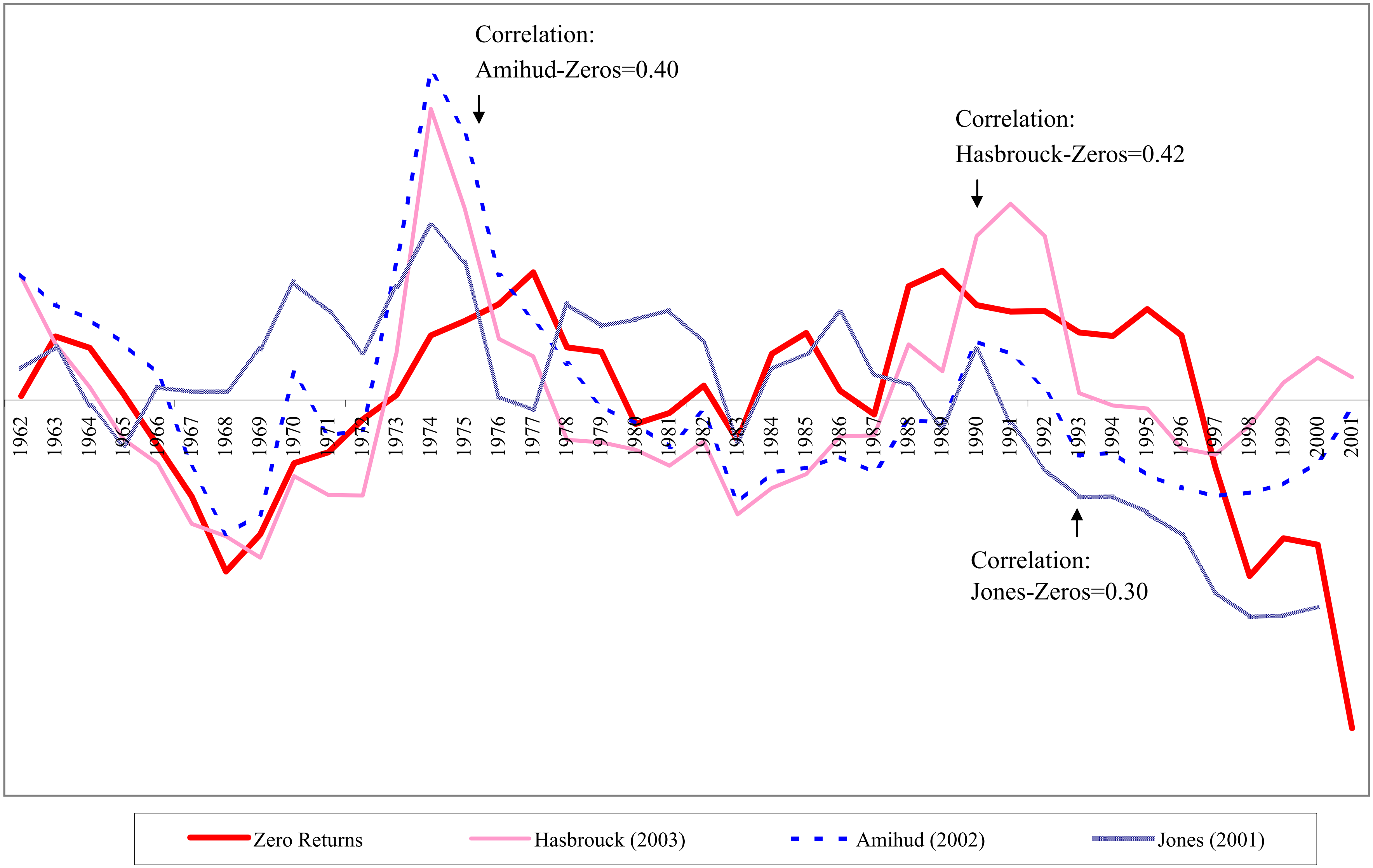

Figure 2

## Return Response to Liquidity Improvement

*Sample I: 1990.01-2001.05*

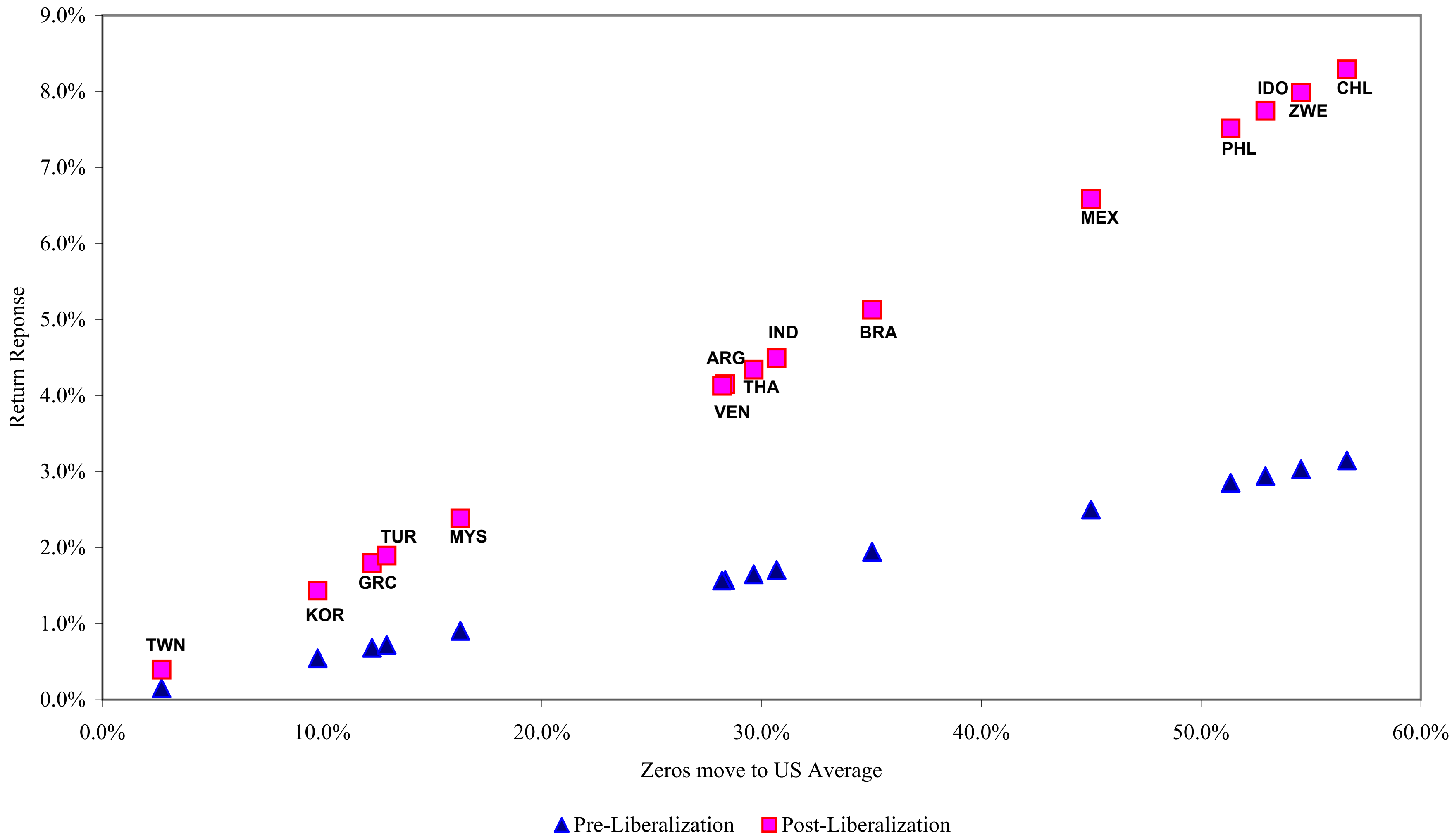

Figure 3

Expected Return Reponse to Liquidity Improvement

*Sample I: 1990.01-2001.05*