Liquidity and short-run predictability: Evidence from international stock markets

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ABSTRACT

This study investigates the determinants of short-run predictability in international stock markets, where predictability is defined as the accuracy of the best-combined daily forecasts. Contrary to popular belief, illiquid markets, characterized by high transaction costs and large price impact, are not necessarily highly predictable. Instead, markets with larger trading volume are more predictable, especially after the global financial crisis and in emerging markets. Those with larger market capitalization, steeper upward trends, and positively skewed returns are less predictable. Company financial strength has limited influence. During the COVID-19 pandemic the markets have become more predictable, with stronger price trends. Emerging markets are less predictable when relatively over- or undervalued.

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G14

G17

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1. Introduction

Return predictability in financial markets may be either a rational feature or an anomaly (De Roon & Szymanowska, 2012). Rational investors include risk premiums as part of their asset pricing models (Fama & French, 2012; Liu & Zhang, 2008; Sagi & Seasholes, 2007), which can explain predictability. For instance, an (il)liquidity premium arises if investors require higher future returns for less liquid assets (Amihud, Hameed, Kang, & Zhang, 2015). When this risk premium varies over time, illiquidity can in part predict asset returns, just as economic risk does (Hammami & Zhu, 2020; Henkel, Martin, & Nardari, 2011; Shamsuddin & Kim, 2010). Other risk premiums include size, value, and momentum premiums (Fama & French, 2012). However, rational pricing models do not sufficiently explain predictability and its changes (De Roon & Szymanowska, 2012; Kirby, 1998).

Market frictions can make returns predictable in otherwise rational and informationally efficient markets. For example, transaction costs can delay the incorporation of information into the prices of stocks (Hou & Moskowitz, 2005) and make the relation between risk factors and expected returns fail to hold (Bali, Peng, Shen, & Tang, 2014). Transaction costs also prevent arbitrageurs from exploiting price differentials. For example, small-cap stocks can take longer to incorporate information than large-cap stocks, and this inefficiency generates a predictability that can be exploited by index arbitrage (Lo & MacKinlay, 1988), but the higher transaction costs for small-cap stocks can prevent such exploitation. Other examples of market frictions include taxes, short-selling constraints, and nonsynchronous trading (Bris, Goetzmann, & Zhu, 2007; DeGennaro & Robotti, 2007; Lo & Craig MacKinlay, 1990).

Behavioral biases can also make pricing inefficient and thus generate a predictable pattern (Barberis, Shleifer, & Vishny, 1998; Daniel & Titman, 1999). De Bondt and Thaler (1985) first challenged the efficient market hypothesis by showing that the stock market transmits investor emotions and biases. For example, among many known biases, such as those reported by Barberis and Thaler (2005) and Hirshleifer (2001), limited investor attention and attention constraints are known to cause underreaction to information (Ben-Rephael, Da, & Israelsen, 2017; Jiang & Zhu, 2017). And underreaction to stock-level liquidity shocks can lead to predictability (Bali et al., 2014). On the other hand, overconfidence, potentially associated with self-attribution bias, can make markets less efficient by creating mispricing and return predictability while inflating trading volume (Odean, 1999). Baker and Stein (2004) found that investors who are overconfident about private information boost liquidity at the same time. However, Ko and Huang (2007) demonstrated that overconfidence generally improves market pricing, and García, Sangiorgi, and Urošević (2007) reported that it does not affect market efficiency and prices. Other biases include loss aversion (Kahneman & Tversky, 1979), which induces investors to keep losing investments and sell profitable stocks. It can also explain deviations from market efficiency (Coval & Shumway, 2005) but may increase market liquidity (Pasquariello, 2014).

All three of these strands of the literature highlight the importance of (il)liquidity in creating predictability—as a risk premium, a type of market friction, and a measure of behavioral biases. Liquidity is generally defined as the ease of trading a large quantity of stocks at a low cost in a short time (Chang, Chen, & Zolotoy, 2017) without adversely affecting their prices (Sarr & Lybek, 2002). In this sense, liquidity or illiquidity is commonly measured by transaction costs or price impact. It follows that higher illiquidity should increase the predictability of individual stock prices, even with informed traders. For example, excessive transaction costs may prevent even informed traders from revealing their information (Lee, 1998), since the costs can outweigh the informational advantage (Cipriani & Guarino, 2008) regardless of their belief convergence (Romano, 2007). Chung and Hrazdil (2010a 2010b) suggest that increased liquidity enhances market efficiency, as new information, facilitated by liquidity, allows prices to reflect more information about fundamentals of firms listed in the NYSE and NASDAQ. A similar result has also been reported by Lagoarde-Segot and Lucey (2008) and Hodrea (2015), who study the MENA and the Bucharest Stock Exchange, respectively, and find that market liquidity increases informational efficiency. Still, there is as yet no comprehensive study of the role of illiquidity in predictability in international markets. Studies of the determinants of predictability and efficiency often cover international markets but rarely include specific liquidity measures (e.g., Ben Rejeb & Boughrara, 2013; Rahman, Khan, Vigne, & Uddin, 2021; Shansuddin & Kim, 2010).

On the other hand, illiquidity does not necessarily entail return predictability (Chordia, Roll, & Subrahmanyam, 2008). In some theoretical models (Glosten & Milgrom, 1985; Kyle, 1985), prices are martingales, i.e. unpredictable, while illiquidity exists as the difference between buying and selling prices, as long as market makers are risk-neutral. Likewise, market frictions do not imply that the markets would be inefficient and predictable, because prices can still reflect all public information (semi-strong-form efficient), but different amounts of private information (DeGennaro & Robotti, 2007; Kyle, 1985). Furthermore, larger transaction costs for individual stocks can be a sign of less-able market makers, who tend to misprice and thus have a strong incentive to increase the spreads (Chordia et al., 2008). Such spreads would attract more arbitrageurs, who can decrease predictability even given wider spreads. On the other hand, higher transaction costs can increase the proportion of information to noise in prices. If market participants trade only when the marginal profits of acting on the information exceed marginal transaction costs (Fama, 1991), informed traders are more likely to trade than noise traders. The market then becomes more efficient and less predictable. On the other hand, more noise trading in proportion to information can raise liquidity but make the markets less efficient (Black, 1986). A significant amount of research has evidenced that noise traders are indeed involved in liquidity trading (e.g. Dow & Gorton, 1993; Foster & Viswanathan, 1993; Pagano & Röell, 1996). Some international evidence also exists regarding a negative relationship between liquidity and predictability, for example in South Africa (Young & Auret, 2018).

Other factors are also known to affect predictability, such as market development, financial strength, and other risk premiums. First, trading volume and market capitalization, representing the level of market development, can explain predictability. Larger trading volume is likely to be accompanied by higher market efficiency (Chordia, Roll, & Subrahmanyam, 2011), but it can also make returns less predictable (Bissoondoyal-Bheenick & Brooks, 2010; Chung & Hrazdil, 2010a). Market capitalization can influence predictability, for example through the size premium, but less so than trading volume or in an opposite direction (Chung & Hrazdil, 2010a). Second, a firm's financial strength is linked to its future stock market returns (Bai, Philippon, & Savov, 2016; Chen, Goldstein, & Jiang, 2007; Lin, 2018). For example, cash flow per share is known to have stronger predictive power (Koijen & Van Nieuwerburgh, 2011) than other similar measures such as price-to-earnings, price-to-sales, and price-to-book ratios (Wang, Liu, Ma, & Diao, 2018). Financial strength is also linked to relative market valuation or value premium. Third, the moments of the return distribution, such as average past return and its skewness, are related to predictability. For example, feedback traders reacting to past price trends tend to create predictability (Sentana & Wadhwani, 1992). Skewness is also known to have predictive power (Amaya, Christoffersen, Jacobs, & Vasquez, 2015), since it can capture the impact of regulations such as short-selling constraints (Bris et al., 2007). Last, slow release of private information can lead to predictability (see, e.g., Cremers et al., 2010). If the values of these determinants change over time, predictability will also change (Lim & Brooks, 2011). These factors can be further categorized by the subset of information they deliver, such as private, public, or past-price-related information.

This study focuses on the impact of (il)liquidity and other determinants on short-run market-level predictability. We measure short-run predictability by the accuracy of univariate forecasting models of returns rather than particular asset pricing models. This approach has the following benefits. First, our study practically defines predictability in its strongest form. It uses the minimum amount of information—a series of past prices or even only the last observed price. Next, it avoids the joint-hypothesis problem of testing a model of equilibrium (Fama, 1991), i.e. an asset-pricing model, for market efficiency or predictability. Last, it minimizes the impact of the economic variables that are used in studies of long-term predictability (Lin, 2018; Wang et al., 2018; Zhu & Zhu, 2013) where monthly or quarterly data are adopted. Studies of weak-form efficiency or trading rules also commonly measure predictability through past prices, but they do not further link predictability specifically to liquidity or transaction costs. For example, studies mostly employ transaction costs as an external hurdle to check whether forecasting models can turn predictability into actual profits (Lin, 2018; Park, 1995; Pesaran & Timmermann, 1995; Zhang, Zeng, Ma, & Shi, 2018).

In addition, our approach provides a more controlled environment. First, by focusing on market indices, we can effectively dismiss the impact of limited investor attention, one of the main behavioral sources of underreaction causing stock-level predictability (Bali et al., 2014; Chung & Hrazdil, 2010b). For example, U.S. investors can be safely assumed to pay most attention to local market indexes, such as the S&P 500. Second, we can largely rule out the existence of informed traders and other behavioral biases related to private information. It cannot be realistically expected that any investor has private information about the entire stock market of a whole country. Last, a market index is by definition a weighted portfolio of individual stocks, so the effects of noise or nonsynchronous trading are minimized.

Therefore, this study essentially identifies the circumstances in which the strongest form of short-run predictability is expected to be higher or lower, while controlling for private information about individual stocks and certain behavioral biases. Our main hypotheses are as follows. First, illiquidity affects return predictability. The relationship will be positive if stronger illiquidity, represented by higher transaction costs, hinders the aggregation of information into prices; it will be negative if transaction costs cause prices to convey more information than noise or attract more arbitrageurs (Chordia et al., 2008; Cipriani & Guarino, 2008; Glosten & Milgrom, 1985; Glosten & Harris, 1988). Second, the relationship is nonlinear. Increasing transaction costs soon discourage noise traders but only later inhibit informed ones (Fama, 1991; Lee, 1998). Third, other factors also determine predictability: market development, company financial strength, and other market and return characteristics. Each identified factor can show what kind of information is slowly delivered to the markets, and thus contribute to predictability. Last, the relationship between predictability and its determinants changes over time and across markets.

In sum, our study contributes to the existing literature as follows. First, we present new evidence on the roles of (il)liquidity in generating return predictability and revisit the previous findings. Second, we present a new measure of strongest-form predictability using the best combined forecasts of price. Third, we provide new evidence on the role of other determinants such as market characteristics, firm fundamentals, and return moments in a more controlled environment. Fourth, as a result, this study also sheds new light on the strands of research on asset pricing and market frictions. Last, our study is one of the few to systematically analyze a panel of international markets to identify the determinants of short-term predictability.

The remainder of the paper is structured as follows: section 2 explains the method, and section 3 describes the data. The results and discussion are presented in section 4. Section 5 concludes.

2. Method

We measure the illiquidity of the stock markets by three proxies. The high-low spread (Corwin & Schultz, 2012) is a transaction-cost-based measure for illiquidity that aims to approximate bid-ask spreads. It utilizes the fact that daily high (low) price is initiated by a buyer (seller) and the spread component of the ratios between daily high and low prices does not change over different time intervals. The high-low spreads (HILO) for daily bid-ask spreads are obtained as a function of these ratios over 1-day and 2-day intervals as below.

$$HILO_t = 2(e^{\alpha} - 1)/(e^{\alpha} + 1), \qquad \text{where}$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}; \qquad \beta = \ln\left(\frac{P_t^H}{P_t^L}\right)^2 + \ln\left(\frac{P_{t-1}^H}{P_{t-1}^L}\right)^2; \tag{1}$$

$$\gamma = \ln\left(\frac{\max(P_t^H, P_{t-1}^H)}{\min(P_t^L, P_{t-1}^L)}\right)^2.$$

P^H and P^L are daily high and low prices, and t is the time indicator. A larger value indicates higher transaction costs and thus stronger illiquidity. The high-low spread is known to reflect actual intraday bid-ask spreads fairly well (Corwin & Schultz, 2012; Marshall, Nguyen, & Visaltanachoti, 2015). The second measure of illiquidity follows Amihud (2002) and Kyle (1985). It is a price-impact-based measure for illiquidity. The daily value of Amihud illiquidity (AMHD) is calculated as a ratio of the absolute return to the trading volume on that day. More illiquid markets are likely to show a larger price impact for the same amount of trading volume. That is, a higher value of AMHD indicates stronger illiquidity. AMHD is known to be positively related to variables that measure illiquidity (Amihud, 2002; Brennan & Subrahmanyam, 1996) and represents the multidimensional aspect of illiquidity well

(Amihud & Noh, 2021). Despite a recent debate as to whether the volume component of AMHD is sufficient to explain its link to future returns (Lou & Shu, 2017), the whole AMHD arguably outperforms the volume component in estimating market illiquidity shocks (Amihud & Noh, 2021). The last measure is the Roll spread (1984), which measures daily bid-ask spreads using negative covariance in successive price changes: $ROLL_t = 2 \times \sqrt{-cov(\Delta P_t, \Delta P_{t-1})}$. However, the Roll spread is heavily affected by volatility and often produces a large number of negative spreads. We convert the negative spreads to zeros.

We estimate predictability by a measure based on the performance of univariate forecasting models. Specifically, our measure is the difference between the accuracy of a given forecasting model and that of a naïve forecast, where the naïve forecast is simply the last observation in the in-sample period. Since in efficient markets no forecasting models are expected to beat naïve forecasts, the relative accuracy of univariate forecasting models can show the level of return predictability in its strongest form, which relies only on past local price. Accordingly, we employ univariate time-series models to measure obtain predictability instead of panel data models.

We identify the best forecasting model among our candidate models and measure its relative performance. Our candidate models are univariate forecasting models, which require only past returns, and their combinations. Combination methods are known to improve forecasting performance (Aiolfi & Timmermann, 2006). We use four simple, popular base forecasting models. First, autoregressive moving-average (ARMA) models identify the best specification for each market according to the Schwarz information criterion, ARMA(p,q), for the in-sample (estimation) periods with up to five lags. We then generate one-step-ahead forecasts for the out-of-sample (forecast or evaluation) periods as follows.

$$r_{t+1}^{f} = \sum_{l=1}^{p} a_l r_{t+1-i} + \sum_{j=1}^{q} b_j u_{t+1-j} \ , \qquad (2)$$

where r is the percentage log return of stock prices and a and b are the autoregressive and moving average coefficients, respectively. Second, autoregressive models with breakpoints (BRK) allow for potential structural breaks caused by historical events. Applying Bai and Perron's (1998) breakpoint test, we estimate an autoregressive model of order one with a maximum of five optimal breakpoints and calculate the forecasts as below.

$$r_{t+1}^{f} = a_L r_t, \tag{3}$$

where a_L is the autoregressive coefficient of the final regime L just after the last identified breakpoint. Third, the simple exponential smoothing model (Gardner & Mckenzie, 1985) finds an exponentially decreasing optimal weight for previous returns and adopts the last projection as a forecast.

$$r_{t+1}^{f} = \alpha \sum_{s=0}^{t-1} (1-\alpha)^s r_{t-s}, \tag{4}$$

where α is the smoothing constant, which is estimated by minimizing the sum of squares of one-step forecast errors. Last, the historical average model uses the average returns in the in-sample periods as forecasts for the entire out-of-sample period.

$$r_{t+1}^{f} = \sum_{t=1}^{T} r_t / T, \tag{5}$$

where T is the last observation in the in-sample period.

To improve accuracy further, we then combine these forecasts. The combination methods aim either to find the optimal weights of individual forecasting models *m* (w_m) in the combined forecasts (r^C) or to choose a specific forecast from the candidates. For instance, the combined forecast for time t+1 in the out-of-sample period is

$$r_{\mathrm{t+1}}^{C} = \sum_{m=1}^{N} w_{m,\mathrm{t+1}} r_{m,t+1}\ , \tag{6}$$

where N is the number of different forecasts to combine.

We test five combination methods. First, the median method chooses the median from all the individual forecasts at each time point of the out-of-sample forecast period. Second, the equal-weight or mean method similarly finds the average of all forecasts. These simple approaches can provide competitive forecasts (Armstrong, 2001). Third, the mean square error (MSE) combination method finds the weights that minimizes the variance of the combined forecast errors. Its calculation requires a training period before the out-of-sample period. The weights are approximately calculated following the proposal of Bates and Granger (1969). We test two-, three-, and four-way combinations. Fourth, the MSE rank method (Aiolfi & Timmermann, 2006) ranks the individual forecasts according to the size of MSE. Then, the weight of each forecast is calculated as the proportion of the inverse of its rank to all forecasts. Last, the information-criterion method calculates the weights based on the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) from the forecasting models (Burnham & Anderson, 2002), as the proportion of $\exp(-0.5 \times \text{AIC or BIC})$ of each forecast over all forecasts.

Then, we measure root mean square errors (RMSE) to select the single or combined forecasting model that performs best against the naïve forecast. The relative predictability of the forecasting model m is calculated as $(\mathrm{RMSE}_{\text{naïve}} - \mathrm{RMSE}_{\mathrm{m}})/\mathrm{RMSE}_{\text{naïve}}$, where $\mathrm{RMSE}_{\text{naïve}}$ is from the naïve forecasts. This measure is also known as the out-of-sample R^2 ($\mathrm{R}^2_{\mathrm{OOS}}$). We choose the forecasting model with the largest $\mathrm{R}^2_{\mathrm{OOS}}$ and define its $\mathrm{R}^2_{\mathrm{OOS}}$ as the measure of predictability.

The predictability measure (PD) is calculated over the entire sample period by the rolling-window method, which is one of the standard methods to study time-varying predictability or weak-form market efficiency (Lim & Brooks, 2011). Illiquidity and the other determinants are calculated in the same way. This procedure is repeated for all stock markets to generate a panel dataset. Finally, we estimate the relationship between the measures of predictability and illiquidity (ILLQ) as follows:

$$PD_{it+1} = c + \beta_1 ILLQ_{it} + \beta_2 ILLQ_{it}^2 + \sum_{k=2}^{K} \beta_k \, DETR_{kit} + v_{it}, \qquad (7)$$

where DETR is the other determinants of predictability, β's are the coefficients, i is the market indicator, and v is the error term.

We adopt three estimation methods for our panel data models. First, we use a fixed-effect method (FX) with robust standard errors. However, if unobserved heterogeneity is correlated with explanatory variables, the estimates can be inconsistent. Furthermore, our dataset may not be free from autocorrelation and heteroscedasticity because financial data are interconnected. Second, we therefore also use an instrumental variable method for dynamic panel data, system GMM (generalized method of moments). The original GMM estimators (Arellano & Bond, 1991), known as difference GMM, are for situations with unobserved heterogeneity, heteroscedasticity, and autocorrelation in a dynamic structure. Difference GMM uses lagged values as instrumental variables to construct more efficient estimates than the original GMM. Arellano and Bover (1995) and Blundell and Bond (1998) developed it into system GMM, which additionally adopts lagged differences as stronger instruments. System GMM is more beneficial in dealing with endogeneity, specifically under potential nonstationarity. However, like FX, it pools the slope coefficients over the cross-sections. Last, we use the mean group (MG) estimator (Pesaran & Smith, 1995). If each cross-section has long observations, the MG estimator is known to produce consistent estimates of the average of the parameters. Also, one can reliably estimate the parameters in individual cross-sections without pooling them.

3. Data

The sample period covers June 1, 2002 to March 31, 2021 and comprises 4,913 daily observations. The price data, collected from Morgan Stanley Capital International (MSCI), include the MSCI single stock market indices of 35 countries. We also collect high and low prices of the day to calculate (il)liquidity. The percentage log returns are obtained using the last index value of each day. The stock indices in this study are based on the market-cap-weighted averages of individual stock prices. Thus, the illiquidity measured directly from the indices can be regarded as a proxy for the market-cap-weighted average of the bid-ask spreads of individual stocks where the spread data for individual stocks are not available in the sample markets. Following the classification of MSCI, we categorize the market indices into 15 developed, 16 emerging, and 4 frontier markets. In addition to the whole sample we analyze two groups of markets, developed and emerging, separately; we do not separately analyze frontier markets for lack of sufficient data. We define three subperiods: pre–global financial crisis, postcrisis (from April 2009, just past the lowest postcrisis point of the S&P 500, until the end of 2018), and pandemic (from 2019, when the virus was spread and detected, to 2020–2021, when the pandemic fully unfolded). Table 1 lists the stock market indices and presents their descriptive statistics.

<Insert Table 1 here>

This study uses 250-day rolling windows (meant to capture roughly a year's worth of data) to generate series of predictability and other variables. This window size is often used in studies of daily data covering about 20 years (Chevallier, Nguyen, Siverskog, & Uddin, 2018; Fratzscher, 2002), although a wider window of around 5 to 15 years is chosen for monthly data (Lin, 2018; Wang et al., 2018; Zhu & Zhu, 2013). The first 200 observations in the window are used as the in-sample period. The next 25 observations are used as the training or holding-out period to generate the weights for combination forecasting methods. The last 25 observations are used as the out-of-sample period to calculate predictability. This window moves by 25 days; eventually, 187 observations are obtained for each market.

In addition to illiquidity, we include the following determinants of predictability identified in the literature reviewed above: trading volume, market capitalization, price-to-book ratio, cash flow per share, average return, and its absolute value and skewness. All of the market and firm fundamentals are market-cap-weighted averages for the constituent companies in the corresponding stock indices. We normalize all variables as the proportional distance from the minimum to the maximum over time. The price-to-book ratio is centered, and its absolute values are used to capture the effect of over- or undervaluation. To identify the nonlinear impact of illiquidity, we also add the squared value of illiquidity.

4. Results and discussion

Compared to naïve forecasts, our models predict returns for our sample data fairly well (Table 2). The best forecasting model in our sample is the median method, in accord with some earlier findings that sophisticated forecasting models (Welch & Goyal, 2008) or combination methods (Jordan, Vivian, & Wohar, 2014; Timmermann, 2006) perform less well than simpler models like historical averages or mean averaging. Thus, in subsequent analyses we use the estimated predictability from the median method. The Appendix presents detailed data on the performance of all forecasting models tested. The predictability yielded by our best forecasting model varies considerably across the sample markets (Table 2), but developed markets (DEV) are on average as predictable as less developed ones (EMG and FRT), despite the common expectation that less-developed markets are less efficient and so more predictable. However, Auer (2016) and Ben Rejeb and Boughrara (2013) argue that emerging markets are at least as efficient as developed ones since the former have begun to evolve, and some studies show that market development conduces to predictability (Hadhri & Ftiti, 2017; Hjalmarsson, 2010; Jordan et al., 2014).

Predictability also varies considerably over time (Figure 1); and again, there is little difference between the developed and emerging markets. Predictability even becomes negative in certain periods, like the global financial crisis in 2007–2008—that is, naïve forecasting cannot be beaten. The impact of the COVID-19 pandemic on predictability is also clear in Figure 1. The pandemic reduces predictability in the stock markets as strongly as does the global financial crisis, but in both episodes predictability recovers soon, implying that predictability is mean-reverting.

<Insert Table 2 here>

<Insert Figure 1 here>

Illiquidity also varies across markets (Table 2), but the degree of variation depends on the specific measure of illiquidity. High-low spreads (HILO) on average do not differ meaningfully between developed and less developed markets, but the Amihud illiquidity (AMHD) is considerably larger in several emerging and frontier markets. The size of Roll spreads is rather mixed across market groups. This difference arises partly because each measure focuses on a different aspect of illiquidity—for example, HILO on transaction costs and AMHD on price impact. Consequently, the choice of illiquidity measure can greatly affect the estimated relationship between liquidity and predictability.

Illiquidity clearly varies over time (Figure 2), as do the gaps between developed and less developed markets. For example, the difference in HILOs occasionally tightens, as it does around the 2007–2008 global financial crisis and the COVID-19 pandemic. The AMHD for emerging markets decreases significantly after the mid-2000s, while the ROLL for both market groups becomes more volatile. This indicates that subsample analysis may be required, with the sample split between before and after the global financial crisis, and before and during the COVID-19 pandemic.

<Insert Figure 2 here>

Illiquidity has a positive relationship with predictability (Table 3), but the evidence is limited rather than universal. In other words, it cannot be easily concluded that more illiquid markets will be more predictable. One of the potential reasons is that the role of illiquidity could differ strongly across the sample markets and over time, as the variation of illiquidity itself indicates. In addition, two forces of illiquidity may have mixed impacts. For example, higher illiquidity or a larger spread slows down the incorporation of information into prices (Cipriani & Guarino, 2008; Glosten & Harris, 1988; Glosten & Milgrom, 1985), and thus increases predictability. At the same time, higher costs can increase the proportion of arbitrageurs (Chordia et al., 2008) and reduce that of noise traders (Fama, 1991), potentially reducing predictability. Even at the market-index level, higher transaction costs can halt index arbitrage (Lo & MacKinlay, 1988). These two opposing forces may also make the relationship between illiquidity and predictability nonlinear, but the evidence is limited.

<Insert Table 3 here>

Other determinants of predictability have more consistent relationships. First, trading volume (TVOL) is clearly positively linked to predictability. This finding may be surprising, since other researchers argued that larger trading volume may speed up the incorporation of information into prices (Chung & Hrazdil, 2010b; Kyle, 1985) or reflect excessive signals coming to the markets (Hartmann, 1999), thus reducing predictability. Our finding of a positive relationship may in part reflect the link between market development and long-term market predictability (Hjalmarsson, 2010; Jordan et al., 2014). Also, it strengthens the evidence of a link between trading volume and future returns (Chen, 2012; Chen, Firth, & Rui, 2001; De Roon & Szymanowska, 2012; Lee & Rui, 2000, 2002; Pisedtasalasai & Gunasekarage, 2007; Rashid, 2007). If this link alone is sufficient to explain the pricing of illiquidity (Lou & Shu, 2017), it may also explain the much stronger influence of trading volume over our three illiquidity measures. Our evidence runs counter to both Amihud and Noh’s (2021) argument that Amihud’s illiquidity measure explains future returns better than its trading volume component, and several findings that trading volume is not significantly linked to future returns (e.g., Chuang, Kuan, & Lin, 2009; Gebka & Wohar, 2013; Saatcioglu & Starks, 1998). Instead, our evidence is consistent with studies showing that return predictability does vary with trading volume (Bissoondoyal-Bheenick & Brooks, 2010; Chung & Hrazdil, 2010a).

Second, larger or developed markets (those with higher market capitalization [MCAP]) are less predictable regardless of illiquidity measures and estimation methods, despite the mixed descriptive evidence in Figure 2. This negative relationship is not consistent with findings based on monthly or quarterly data (Hadhri & Ftiti, 2017; Hjalmarsson, 2010; Jordan et al., 2014) but is in line with other findings based on daily data (Chordia et al., 2011; Chung & Hrazdil, 2010a; Risso, 2009; Sakalauskas & Kriksciuniene, 2011). Although recent cross-country studies show that emerging markets can be more efficient than developed markets (e.g., Auer, 2016), our analytical evidence suggests that this may not be the case. On the other hand, market capitalization and trading volume may have opposite impacts on predictability because they may represent different aspects of market development—size and activity. This could be another reason for the mixed evidence in the earlier studies.

Third, financial strength in terms of cash flow per share (CF) has an insignificant relationship with predictability. This finding contrasts with company-level evidence that companies with more substantial cash flow can increase stock returns in the long term (Bai et al., 2016; Chen et al., 2007; Koijen & Van Nieuwerburgh, 2011; Lin, 2018), perhaps because our study focuses on short-term and market-level predictability.

Fourth, over- or undervalued markets (PB) have largely lower predictability. It can be argued that excessive valuation may trigger unexpected market movement, which cannot be easily captured by forecasting models. Although this relationship is relatively weak, it confirms the role of relative valuation in predictability (Wang et al., 2018). Likewise, market trends that are strong in sign (MEAN) or magnitude (|MEAN|) reduce predictability. Particularly, our results suggest that rising stock markets make returns much less predictable.

This supports the findings of Henkel et al. (2011) and Rapach et al. (2013) that stock returns are more predictable during an economic downturn. However, the role of feedback traders in creating predictability (Sentana & Wadhwani, 1992) is in doubt at least at the market level. Last, the skewness of return (SKEW) reduces predictability, perhaps because more frequent extreme shocks or short-selling constraints (Bris et al., 2007) reduce the predictability of markets.

On the other hand, short-term predictability (Figure 1) may be too volatile to be fully explained by relatively slowly changing illiquidity (Figure 2) and other determinants. Therefore, we reestimated the same models on the moving average of current and past three observations of predictability, which covers a calendar quarter instead of a month. The results (Table 4) are mostly consistent with the findings in Table 3: we still observe a weak and nonlinear effect of liquidity, a positive impact of TVOL, and a negative impact of MCAP, MEAN, and SKEW. The noticeable changes are that CF now increases predictability, though rather weakly. That is, company fundamentals are better associated with longer-term predictability, but not strongly with short-term predictability, probably because of their link to future stock returns (Bai et al., 2016; Chen et al., 2007; Koijen & Van Nieuwerburgh, 2011; Lin, 2018). PD(-1) still has strong positive significance, which shows momentum in predictability.

<Insert Table 4 here>

As Figures 1 and 2 show, the global financial crisis in 2007–2008 may have caused structural changes in the international stock markets and may also have affected the relationship between market predictability and its determinants. We therefore repeat the same analysis on the precrisis and postcrisis subsamples (defined in section 3). Table 5 shows that the relationship largely does not differ in any subperiod. One noticeable change is that TVOL has a much stronger positive relationship with predictability after the crisis period than before. That is, particularly after the global financial crisis, it is difficult to say that larger trading volume increases the informativeness of prices and thus market efficiency, as some earlier writers have argued (Chung & Hrazdil, 2010b; Kyle, 1985). Instead, the link between trading volume and future returns is strengthened after the crisis. On the other hand, illiquidity has a slightly stronger and nonlinear impact on predictability, but only for a certain liquidity measure and subperiod.

<Insert Table 5 here>

Another potential structural change is the COVID-19 pandemic in 2020–2021. It decreased predictability as strongly as did the global financial crisis (Figure 1), and it caused a surge in illiquidity (Figure 2). We investigate the subperiod that includes the pandemic separately (Table 6). Most of the results are consistent with the full-sample results (Table 3) in terms of the sign and significance of each determinant of predictability. One exception is that market trend (|MEAN|) increases predictability, perhaps because strong and prolonged bear markets during the pandemic increased short-term predictability. Company fundamentals (CF) become irrelevant during this period although their effect was already weak. Regulation constraints (SKEW) also has much less effect.

<Insert Table 6 here>

Stock markets with differing degrees of development may have different relationships between predictability and its determinants. For example, predictability shows sporadic gaps between developed and emerging markets, and illiquidity in emerging markets is generally much higher and varies widely (Figures 1 and 2). Although we controlled for this impact by including TVOL and MCAP, it is worthwhile to conduct a subgroup analysis of the two groups of markets. Our results in Table 7 show that most of the determinants of predictability do not differ between the two groups. However, the strong positive relationship between predictability and TVOL seen in the earlier results actually originates from emerging markets. That is, in emerging markets a strong link between trading volume and future returns can arise, perhaps because of institutional or behavioral factors other than financial strength or market characteristics tested in this study. Also, PB is one of the main determinants of predictability only in the emerging markets, where relative valuation may not be instantly reflected in prices as it is in developed markets.

<Insert Table 7 here>

5. Conclusion

Whereas other studies have highlighted the importance of illiquidity to the market-level predictability of stock returns, we found that more illiquid markets do not necessarily have more predictable returns. Instead, other determinants are more consistently and strongly linked to predictability. More actively traded markets are generally more predictable, while those with larger market capitalization, rising prices, and positively skewed returns are less so. Company financial strength has limited influence. Trading volume increases predictability even more strongly after the global financial crisis, as do stronger market trends during the COVID-19 pandemic. The impact of trading volume arises mostly in emerging markets, as does that of relative valuation.

Our findings enrich the literature on the relationship between return predictability and its determinants as well as the literatures on market efficiency and liquidity. Additionally, this study offers pertinent information to fund managers and other practitioners seeking predictable returns in international stock markets. Our results call for caution in studies of illiquidity using a single liquidity measure and estimation method. An extension of this analysis would be to expand the investigation into different measures of illiquidity and other forms of nonlinear relationships with predictability. As Rapach et al. (2013) suggested, future research could also test more determinants in the global context.

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Table 1

Descriptive statistics of sample markets.

Dev	Country	Mean	SD	Skew	MCAP
WLD	World Index	0.0223	0.9120	-0.3823	31,600,000
DEV	Austria	0.0047	1.6323	-0.2452	64,065
	Belgium	0.0066	1.3518	-0.2471	238,458
	Denmark	0.0446	1.2711	-0.3094	190,908
	Finland	0.0084	1.5822	-0.3089	157,478
	France	0.0139	1.3838	-0.2147	1,636,380
	Germany	0.0193	1.4035	-0.2374	1,203,834
	Ireland	-0.0018	1.5968	-0.3644	69,175
	Israel	0.0162	1.1771	-0.3670	90,077
	Italy	-0.0041	1.5364	-0.3580	496,251
	Netherland	0.0208	1.2887	-0.2473	434,520
	New Zealand	0.0221	1.2195	-0.2410	22,909
	Norway	0.0164	1.6790	-0.3280	168,100
	Portugal	-0.0032	1.3412	-0.1871	51,960
	Spain	0.0067	1.5179	-0.2936	548,444
	USA	0.0280	1.0610	-0.3270	16,100,000
EMG	Chile	0.0180	1.3168	-0.1600	116,155
	China	0.0396	1.4949	-0.1567	1,954,663
	Colombia	0.0401	1.6139	-0.3163	69,861
	Czech	0.0163	1.4883	-0.2870	30,699
	Egypt	0.0425	1.7330	-0.8385	22,315
	Greece	-0.0590	2.2425	-0.1968	52,426
	Hungary	0.0196	1.9421	-0.2290	21,535
	India	0.0417	1.7415	-0.2372	177,271
	Indonesia	0.0391	1.4852	-0.3339	701,049
	Korea	0.0286	1.5674	-0.2488	732,328
	Malaysia	0.0129	0.8923	-0.1309	228,859
	Peru	0.0432	1.6997	-0.2887	36,330
	Philippines	0.0333	1.3791	-0.3020	89,127
	Poland	0.0083	1.7527	-0.2840	89,170
	South Africa	0.0207	1.7713	-0.2594	319,050
	Taiwan	0.0218	1.2912	-0.2653	544,392
FRT	Argentina	0.0277	2.2433	-0.4547	20,749
	Morocco	0.0171	0.9880	-0.0532	32,027
	Mexico	0.0194	1.5083	-0.2801	233,758
	Pakistan	0.0018	1.4522	-0.2000	18,860

Notes: DEV, EMG, and FRT are developed, emerging, and frontier markets, following the MSCI classification of market development. Mean, SD, and Skew are average, standard deviation, and skewness of local stock market indices, respectively, in terms of percentage log returns. MCAP is market capitalization in million $. All statistics are averages over the sample period.

Table 2

Predictability and illiquidity by market.

	Market	Predictability	Illiquidity		
			HILO	AMHD	ROLL
DEV	Austria	0.2103	0.0038	3.5500	0.0445
	Belgium	0.2113	0.0027	1.0100	0.0225
	Denmark	0.2177	0.0031	0.0677	0.0446
	Finland	0.2238	0.0027	0.9610	0.2380
	France	0.2173	0.0032	0.0334	0.0349
	Germany	0.2217	0.0032	0.1930	0.0465
	Ireland	0.2205	0.0026	0.0543	0.0576
	Israel	0.2001	0.0040	0.5820	0.0210
	Italy	0.2712	0.0017	0.2950	0.0545
	Netherland	0.2207	0.0034	0.0153	0.0399
	New Zealand	0.2262	0.0024	0.0911	0.0316
	Norway	0.2207	0.0028	0.2990	0.1251
	Portugal	0.1969	0.0011	0.5340	0.0149
	Spain	0.2217	0.0026	0.3070	0.0089
	USA	0.2361	0.0027	0.0065	0.8702
EMG	Chile	0.2181	0.0024	0.0475	0.0381
	China	0.2355	0.0032	0.0043	0.0008
	Colombia	0.2124	0.0020	8.8600	0.0379
	Czech	0.2101	0.0025	7.0600	0.0027
	Egypt	0.3117	0.0060	3.5100	0.0331
	Greece	0.2025	0.0061	1.5600	0.0100
	Hungary	0.2093	0.0036	4.7900	0.0009
	India	0.2566	0.0033	0.0302	0.0000
	Indonesia	0.2380	0.0031	0.1050	0.0019
	Korea	0.2252	0.0028	0.1290	0.0001
	Malaysia	0.2298	0.0016	0.0508	0.0015
	Peru	0.2173	0.0035	10.3000	0.3199
	Philippines	0.2268	0.0026	0.1170	0.0025
	Poland	0.2173	0.0031	0.8830	0.1085
	South Africa	0.2289	0.0027	0.0054	0.0011
	Taiwan	0.2221	0.0026	0.0884	0.0187
FRT	Argentina	0.2375	0.0047	20.6000	0.8548
	Morocco	0.2011	0.0019	72.7000	0.0006
	Mexico	0.2245	0.0027	0.0882	0.1742
	Pakistan	0.2376	0.0039	0.6570	0.0005
AVG	DEV	0.2211	0.0028	0.5333	0.1103
	EMG	0.2289	0.0032	2.3463	0.0361
	FRT	0.2252	0.0033	23.5113	0.2575
CV		0.0904	0.3265	2.8744	2.0536

Notes: DEV, EMG, and FRT are developed, emerging, and frontier markets, following the MSCI classification of market development. HILO is Corwin and Schultz’s (2012) high-low spread. AMHD is Amihud’s (2002) illiquidity measure, and ROLL is Roll’s (1984) spread. CV is the coefficient of variation over cross-sections.

Table 3

Illiquidity and the determinants of predictability.

	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.0499	0.0630	0.1301 *	-0.0365	0.0837 *	0.0049	0.0112	0.0160	0.0109
	(0.0369)	(0.0448)	(0.0682)	(0.0287)	(0.0436)	(0.0603)	(0.0244)	(0.0330)	(0.0283)
ILLQ2	0.0222	0.0142	-0.0189	-0.0046	-0.0913 **	0.0087	-0.0339	-0.0424	-0.0312
	(0.0393)	(0.0469)	(0.0727)	(0.0288)	(0.0423)	(0.0484)	(0.0393)	(0.0578)	(0.0438)
TVOL	0.0655 *	0.0843 **	0.4795 ***	0.0650 *	0.1084 ***	0.6189 ***	0.1172 ***	0.1081 **	0.6050 ***
	(0.0370)	(0.0322)	(0.1738)	(0.0376)	(0.0391)	(0.1920)	(0.0384)	(0.0408)	(0.1843)
MCAP	-0.0674 ***	-0.0467 ***	-0.1500 ***	-0.0921 ***	-0.0589 ***	-0.1948 ***	-0.0837 ***	-0.0593 ***	-0.1765 ***
	(0.0086)	(0.0082)	(0.0267)	(0.0092)	(0.0113)	(0.0235)	(0.0083)	(0.0104)	(0.0237)
PB	-0.0161	-0.0402 **	-0.0164	-0.0097	-0.0450 **	-0.0198	-0.0090	-0.0452 *	-0.0125
	(0.0204)	(0.0185)	(0.0291)	(0.0192)	(0.0220)	(0.0285)	(0.0194)	(0.0227)	(0.0285)
CF	0.0152	0.0074	0.0341	0.0168	0.0089	0.0380	0.0173	0.0077	0.0376
	(0.0096)	(0.0110)	(0.0308)	(0.0106)	(0.0142)	(0.0262)	(0.0109)	(0.0142)	(0.0262)
MEAN	-0.0724 ***	-0.0666 ***	-0.0833 ***	-0.0955 ***	-0.1041 ***	-0.1042 ***	-0.1020 ***	-0.1004 ***	-0.1104 ***
	(0.0079)	(0.0087)	(0.0089)	(0.0086)	(0.0109)	(0.0141)	(0.0085)	(0.0102)	(0.0107)
|MEAN|	-0.0154 *	-0.0188 *	-0.0181 *	0.0251 **	-0.0205	-0.0418	-0.0020	-0.0036	-0.0181
	(0.0087)	(0.0097)	(0.0101)	(0.0120)	(0.0173)	(0.0367)	(0.0071)	(0.0093)	(0.0113)
SKEW	-0.0600 ***	-0.0305 **	-0.0815 ***	-0.0587 ***	-0.0251	-0.0817 ***	-0.0610 ***	-0.0238	-0.0657 ***
	(0.0111)	(0.0126)	(0.0146)	(0.0102)	(0.0155)	(0.0146)	(0.0106)	(0.0159)	(0.0138)
PD(-1)	0.1590 ***	0.1736 ***	0.0944 ***	0.1704 ***	0.1728 ***	0.1086 ***	0.1712 ***	0.1733 ***	0.1081 ***
	(0.0098)	(0.0160)	(0.0103)	(0.0106)	(0.0201)	(0.0112)	(0.0109)	(0.0205)	(0.0109)
N	6481	6481	6446	6481	6481	6446	6481	6481	6446
F	73.93	38.00	4.08	54.02	27.43	3.85	63.81	25.63	3.91

Notes: ILLQ is illiquidity according to the high-low spread (HILO), the Amihud measure (AMHD), and the Roll spread (ROLL), respectively. TVOL, MCAP, PB, and CF are trading volume, market capitalization, price-to-book ratio, and cash flow per share, respectively. MEAN is average return, SKEW is skewness, and PD(-1) is the lagged value of predictability. All figures in italic are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. In GMM, our test results do not reject the null hypothesis (H_0) in the AR(2) and Hansen tests but reject it in the AR(1) test at the 1% level.

Table 4

Illiquidity and the determinants of predictability—moving average.

	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.0629 *	0.0709	0.0733	-0.0682 **	0.0194	-0.0414	-0.0097	-0.0277	0.0093
	(0.0355)	(0.0905)	(0.0641)	(0.0251)	(0.0472)	(0.0623)	(0.0202)	(0.0531)	(0.0331)
ILLQ2	0.0223	-0.0453	0.0867	0.0317	-0.0301	-0.0207	0.0009	0.0112	-0.0215
	(0.0375)	(0.0925)	(0.0695)	(0.0279)	(0.0498)	(0.0970)	(0.0301)	(0.0731)	(0.0436)
TVOL	0.0634	0.0450	0.4479 ***	0.0609	0.0388	0.5801 ***	0.1211 ***	0.0518	0.6107 ***
	(0.0386)	(0.0383)	(0.1701)	(0.0419)	(0.0390)	(0.1954)	(0.0369)	(0.0423)	(0.1529)
MCAP	-0.0456 ***	-0.0049	-0.0998 ***	-0.0732 ***	-0.0083	-0.1760 ***	-0.0655 ***	-0.0052	-0.1615 ***
	(0.0073)	(0.0104)	(0.0291)	(0.0077)	(0.0106)	(0.0216)	(0.0068)	(0.0112)	(0.0210)
PB	-0.0164	0.0118	-0.0376	-0.0083	0.0160	-0.0209	-0.0086	0.0160	-0.0229
	(0.0170)	(0.0139)	(0.0229)	(0.0152)	(0.0142)	(0.0247)	(0.0154)	(0.0136)	(0.0238)
CF	0.0150 *	-0.0142	0.0072	0.0160 *	-0.0149	0.0206	0.0161 *	-0.0141	0.0235
	(0.0078)	(0.0114)	(0.0178)	(0.0092)	(0.0112)	(0.0181)	(0.0092)	(0.0113)	(0.0197)
MEAN	-0.0137	-0.1169 ***	0.0042	-0.0428 ***	-0.1344 ***	-0.0301 ***	-0.0498 ***	-0.1334 ***	-0.0511 ***
	(0.0084)	(0.0177)	(0.0121)	(0.0065)	(0.0192)	(0.0109)	(0.0065)	(0.0191)	(0.0091)
$\vert$MEAN$\vert$	-0.0344 ***	0.0036	-0.0558 ***	0.0142	0.0111	-0.0306	-0.0188 **	0.0109	-0.0387 ***
	(0.0092)	(0.0173)	(0.0113)	(0.0145)	(0.0222)	(0.0362)	(0.0079)	(0.0168)	(0.0127)
SKEW	-0.0269 **	-0.0676 ***	-0.0333 **	-0.0281 ***	-0.0691 ***	-0.0360 ***	-0.0295 ***	-0.0681 ***	-0.0267 **
	(0.0110)	(0.0189)	(0.0141)	(0.0098)	(0.0186)	(0.0125)	(0.0102)	(0.0185)	(0.0123)
PD(-1)	0.7215 ***	1.1237 ***	0.6707 ***	0.7323 ***	1.1489 ***	0.6824 ***	0.7338 ***	1.1468 ***	0.6842 ***
	(0.0040)	(0.0301)	(0.0066)	(0.0043)	(0.0339)	(0.0066)	(0.0042)	(0.0332)	(0.0068)
N	6447	6447	6412	6447	6447	6412	6447	6447	6412
F	6999	218.20	22.42	5393.00	197.40	21.73	5526	204.60	21.80

Notes: ILLQ is illiquidity according to the high-low spread (HILO), the Amihud measure (AMHD), and the Roll spread (ROLL), respectively. TVOL, MCAP, PB, and CF are trading volume, market capitalization, price-to-book ratio, and cash flow per share, respectively. MEAN is average return, SKEW is skewness, and PD(-1) is the lagged value of predictability. All figures in italic are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. In GMM, our test results do not reject the null hypothesis (H_0) in the AR(2) and Hansen tests but reject it in the AR(1) test at the 1% level.

Table 5

Subgroup analysis—pre– and post–global financial crisis.

PRE	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.0253	-0.0256	0.5342 **	-0.1862 ***	-0.0252	-0.2618	0.0893 *	0.1066 **	0.1653
	(0.0575)	(0.0519)	(0.2129)	(0.0471)	(0.0403)	(0.2453)	(0.0517)	(0.0429)	(0.1323)
ILLQ2	0.0852	0.1052 *	-0.6373 **	0.0844 **	-0.0022	0.0134	-0.1821 ***	-0.1917 ***	-0.3706
	(0.0611)	(0.0586)	(0.2910)	(0.0404)	(0.0378)	(0.1102)	(0.0633)	(0.0537)	(0.3036)
TVOL	0.1256 *	0.0277	0.4739	0.0645	0.0488	-1.0157	0.2732 ***	0.0645 *	1.1745
	(0.0700)	(0.0356)	(2.3378)	(0.0576)	(0.0357)	(3.1861)	(0.0620)	(0.0349)	(1.0252)
MCAP	-0.1374 ***	-0.0493 ***	-1.1309 ***	-0.1906 ***	-0.0753 ***	-0.7817 ***	-0.1398 ***	-0.0590 ***	-0.6410 **
	(0.0179)	(0.0131)	(0.4226)	(0.0232)	(0.0147)	(0.2750)	(0.0240)	(0.0112)	(0.2929)
PB	-0.0322	-0.0332	-0.2670	-0.0178	-0.0361	-0.0757	-0.0399	-0.0271	0.0691
	(0.0311)	(0.0238)	(0.2982)	(0.0328)	(0.0231)	(0.1248)	(0.0333)	(0.0205)	(0.1720)
CF	0.0107	0.0009	0.3838 *	0.0319 *	0.0133	0.1495	0.0311	0.0111	-0.0157
	(0.0164)	(0.0160)	(0.2159)	(0.0169)	(0.0172)	(0.1703)	(0.0202)	(0.0153)	(0.1416)
MEAN	-0.0661 ***	-0.0601 ***	-0.1673 ***	-0.0957 ***	-0.0884 ***	-0.1382 ***	-0.1195 ***	-0.1032 ***	-0.1400 ***
	(0.0107)	(0.0111)	(0.0283)	(0.0109)	(0.0092)	(0.0289)	(0.0104)	(0.0094)	(0.0248)
|MEAN|	-0.0366 ***	-0.0347 ***	-0.0656 ***	0.0634 ***	-0.0074	0.0979	-0.0257 **	-0.0161 **	-0.1021 ***
	(0.0098)	(0.0096)	(0.0180)	(0.0217)	(0.0137)	(0.1031)	(0.0113)	(0.0077)	(0.0242)
SKEW	-0.0454 **	0.0160	-0.1982 ***	-0.0023	0.0323 *	-0.1375 ***	-0.0030	0.0254 *	-0.1212 **
	(0.0186)	(0.0193)	(0.0516)	(0.0164)	(0.0166)	(0.0446)	(0.0187)	(0.0146)	(0.0489)
PD(-1)	0.1864 ***	0.2817 ***	0.0498 ***	0.2078 ***	0.2842 ***	0.0729 ***	0.2092 ***	0.2909 ***	0.0723 ***
	(0.0148)	(0.0332)	(0.0185)	(0.0151)	(0.0296)	(0.0175)	(0.0150)	(0.0281)	(0.0160)
N	2456	2456	2421	2456	2456	2421	2456	2456	2421
F	85.98	33.14	3.07	62.72	32.66	2.81	80.14	33.76	3.09
POST	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.1906 ***	0.1769 **	0.6847 **	0.0269	0.0727	-0.0477	-0.0297	-0.0380	0.0122
	(0.0602)	(0.0739)	(0.3377)	(0.0514)	(0.0535)	(0.9018)	(0.0239)	(0.0246)	(0.1047)
ILLQ2	-0.1923 ***	-0.1643 **	-0.7399	-0.0286	-0.0793	2.6271	0.0421	0.0496	-0.1720
	(0.0668)	(0.0791)	(0.5216)	(0.0649)	(0.0659)	(2.4877)	(0.0403)	(0.0377)	(0.2898)
TVOL	0.1611 **	0.0876 **	1.5781 ***	0.1837 ***	0.0943 **	2.8769 ***	0.1630 **	0.0917 **	2.2689 ***
	(0.0673)	(0.0368)	(0.5214)	(0.0638)	(0.0426)	(0.7933)	(0.0646)	(0.0415)	(0.6077)
MCAP	-0.0921 ***	-0.0420 ***	-0.3142 ***	-0.1007 ***	-0.0519 ***	-0.4382 ***	-0.1015 ***	-0.0529 ***	-0.4499 ***
	(0.0155)	(0.0147)	(0.1161)	(0.0148)	(0.0141)	(0.1481)	(0.0147)	(0.0146)	(0.1518)
PB	0.0263	-0.0454	0.1202	0.0298	-0.0361	0.0790	0.0291	-0.0421	0.1043
	(0.0261)	(0.0312)	(0.1171)	(0.0260)	(0.0307)	(0.1351)	(0.0257)	(0.0339)	(0.1255)
CF	0.0137	0.0085	0.1430 ***	0.0132	0.0130	0.1446 ***	0.0131	0.0120	0.1642 ***
	(0.0126)	(0.0104)	(0.0523)	(0.0128)	(0.0098)	(0.0508)	(0.0130)	(0.0102)	(0.0542)
MEAN	-0.0966 ***	-0.0764 ***	-0.0936 **	-0.1072 ***	-0.0990 ***	-0.0888 **	-0.1045 ***	-0.0863 ***	-0.0903 **
	(0.0206)	(0.0214)	(0.0372)	(0.0206)	(0.0208)	(0.0422)	(0.0203)	(0.0200)	(0.0391)
|MEAN|	-0.0157	-0.0240	0.0580 **	-0.0281	-0.0492 **	-0.3324 **	-0.0189	-0.0267 *	0.0512 **
	(0.0135)	(0.0150)	(0.0255)	(0.0226)	(0.0203)	(0.1561)	(0.0135)	(0.0145)	(0.0224)
SKEW	-0.0586 ***	-0.0425 ***	-0.0107	-0.0577 ***	-0.0427 ***	-0.0155	-0.0565 ***	-0.0401 **	0.0037
	(0.0124)	(0.0149)	(0.0286)	(0.0120)	(0.0149)	(0.0296)	(0.0122)	(0.0154)	(0.0301)
PD(-1)	0.1334 ***	0.1602 ***	0.0695 ***	0.1354 ***	0.1577 ***	0.1055 ***	0.1355 ***	0.1576 ***	0.1066 ***
	(0.0165)	(0.0223)	(0.0168)	(0.0166)	(0.0212)	(0.0169)	(0.0166)	(0.0213)	(0.0184)
N	3150	3150	3150	3150	3150	3150	3150	3150	3150
F	37.94	20.15	127.00	31.27	15.24	123.40	31.97	15.19	122.70

Notes: ILLQ is illiquidity according to the high-low spread (HILO), the Amihud measure (AMHD), and the Roll spread (ROLL), respectively. TVOL, MCAP, PB, and CF are trading volume, market capitalization, price-to-book ratio, and cash flow per share, respectively. MEAN is average return, SKEW is skewness, and PD(-1) is the lagged value of predictability. All figures in italic are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. In GMM, our test results do not reject the null hypothesis (H_0) in the AR(2) and Hansen tests but reject it in the AR(1) test at the 1% level.

Table 6

Subgroup analysis—COVID-19 pandemic.

PDM	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.7865 ***	0.4001 **	-1.0327	0.0349	0.1350	0.3013	-0.0851	-0.1164	-1.7771
	(0.1702)	(0.1545)	(2.5476)	(0.1265)	(0.1813)	(2.0444)	(0.0770)	(0.1275)	(1.1577)
ILLQ2	-0.4585 ***	-0.1959	1.2412	-0.0620	-0.1717	-85.2051	0.1403	0.2287	9.0603 *
	(0.1482)	(0.1557)	(3.8605)	(0.1391)	(0.2181)	(107.782)	(0.1000)	(0.1653)	(5.4177)
TVOL	0.3016	0.3833 *	12.6559	1.1227 ***	0.1505	26.7495	1.0797 ***	0.1004	14.0177
	(0.3573)	(0.1979)	(21.9943)	(0.3880)	(0.2960)	(18.9640)	(0.3905)	(0.2592)	(19.0315)
MCAP	-0.2279 ***	-0.1323 **	-1.7184	-0.4304 ***	-0.1125 *	-2.1938	-0.4355 ***	-0.1328 **	-3.4995 **
	(0.0768)	(0.0495)	(2.4331)	(0.1012)	(0.0661)	(1.8199)	(0.0970)	(0.0596)	(1.6178)
PB	0.0585	0.0528	-1.4611	0.1603	0.1436	0.8204	0.1518	0.1040	1.6105
	(0.1030)	(0.1066)	(2.5534)	(0.1207)	(0.1538)	(2.2580)	(0.1238)	(0.1552)	(1.7351)
CF	-0.0528	-0.0246	1.0650	-0.0037	-0.0137	-1.3575	-0.0020	-0.0262	-0.5988
	(0.0747)	(0.0436)	(1.4377)	(0.0850)	(0.0572)	(1.8044)	(0.0866)	(0.0509)	(1.1700)
MEAN	-0.1692 ***	-0.0896	0.0835	-0.1435 ***	-0.0683	-0.0789	-0.1406 ***	-0.0622	-0.0508
	(0.0413)	(0.0589)	(0.1956)	(0.0460)	(0.0696)	(0.2186)	(0.0457)	(0.0652)	(0.1841)
|MEAN|	0.0672 ***	0.0606 *	0.4222 ***	0.0924 **	0.0674	-1.4964	0.0849 ***	0.0908 **	0.2968 ***
	(0.0234)	(0.0300)	(0.1319)	(0.0339)	(0.0556)	(1.2108)	(0.0254)	(0.0410)	(0.1123)
SKEW	-0.0300	-0.0349	-0.1335	-0.0636	-0.1102 *	-0.1984	-0.0527	-0.0755	-0.0117
	(0.0371)	(0.0480)	(0.1704)	(0.0416)	(0.0616)	(0.1962)	(0.0438)	(0.0615)	(0.1489)
PD(-1)	-0.0261	0.0273	-0.3763 ***	0.0281	0.1134 **	-0.3964 ***	0.0250	0.0968 *	-0.3628 ***
	(0.0247)	(0.0389)	(0.0370)	(0.0231)	(0.0495)	(0.0379)	(0.0226)	(0.0486)	(0.0396)
N	875	875	875	875	875	875	875	875	875
F	41.89	30.83	39.36	23.32	13.03	38.65	20.73	12.73	37.23

Notes: ILLQ is illiquidity according to the high-low spread (HILO), the Amihud measure (AMHD), and the Roll spread (ROLL), respectively. TVOL, MCAP, PB, and CF are trading volume, market capitalization, price-to-book ratio, and cash flow per share, respectively. MEAN is average return, SKEW is skewness, and PD(-1) is the lagged value of predictability. All figures in italic are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. In GMM, our test results do not reject the null hypothesis (H_0) in the AR(2) and Hansen tests but reject it in the AR(1) test at the 1% level.

Table 7

Subgroup analysis—developed and emerging markets.

DEV	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.1202 *	0.0483	-0.0307	-0.0434	-0.0080	0.1232	0.0191	0.0226	0.0496
	(0.0604)	(0.0941)	(0.1093)	(0.0370)	(0.0648)	(0.0808)	(0.0373)	(0.0642)	(0.0428)
ILLQ2	-0.0501	0.0103	0.1547	0.0231	0.0103	0.0230	-0.0676	-0.1007	-0.1103 *
	(0.0679)	(0.1069)	(0.1195)	(0.0410)	(0.0754)	(0.0684)	(0.0622)	(0.1119)	(0.0646)
TVOL	-0.0338	0.0274	0.1485	-0.0285	0.0223	0.4122 *	0.0259	0.0404	0.2219
	(0.0356)	(0.0655)	(0.1396)	(0.0352)	(0.0738)	(0.2286)	(0.0426)	(0.0691)	(0.1462)
MCAP	-0.1097 ***	-0.0951 ***	-0.2137 ***	-0.1266 ***	-0.1099 ***	-0.2177 ***	-0.1157 ***	-0.1016 ***	-0.1921 ***
	(0.0105)	(0.0153)	(0.0259)	(0.0118)	(0.0216)	(0.0272)	(0.0109)	(0.0179)	(0.0300)
PB	0.0599 *	0.0410	0.0826 **	0.0495	0.0402	0.0789 *	0.0526	0.0339	0.0745 *
	(0.0326)	(0.0439)	(0.0347)	(0.0324)	(0.0492)	(0.0448)	(0.0310)	(0.0425)	(0.0432)
CF	0.0124	0.0061	-0.0035	0.0091	0.0011	0.0091	0.0176	0.0087	0.0168
	(0.0155)	(0.0271)	(0.0372)	(0.0192)	(0.0320)	(0.0350)	(0.0196)	(0.0301)	(0.0341)
MEAN	-0.0639 ***	-0.0563 ***	-0.0848 ***	-0.0927 ***	-0.0840 ***	-0.1307 ***	-0.1026 ***	-0.0891 ***	-0.1206 ***
	(0.0079)	(0.0136)	(0.0111)	(0.0122)	(0.0236)	(0.0199)	(0.0116)	(0.0204)	(0.0150)
|MEAN|	-0.0072	0.0048	-0.0032	0.0304	0.0163	-0.1561 **	0.0064	0.0201	-0.0119
	(0.0181)	(0.0238)	(0.0191)	(0.0309)	(0.0382)	(0.0614)	(0.0166)	(0.0232)	(0.0213)
SKEW	-0.0633 ***	-0.0495 **	-0.0803 ***	-0.0633 ***	-0.0562 **	-0.0771 ***	-0.0625 ***	-0.0558 ***	-0.0746 ***
	(0.0196)	(0.0224)	(0.0197)	(0.0163)	(0.0191)	(0.0164)	(0.0166)	(0.0184)	(0.0185)
PD(-1)	0.1453 ***	0.1593 ***	0.0855 ***	0.1604 ***	0.1619 ***	0.1011 ***	0.1596 ***	0.1529 ***	0.0962 ***
	(0.0144)	(0.0326)	(0.0154)	(0.0167)	(0.0363)	(0.0160)	(0.0176)	(0.0380)	(0.0146)
N	2790	2790	2775	2790	2790	2775	2790	2790	2775
F	36.63	22.18	2.65	98.74	28.51	2.42	72.45	300.70	2.57
EMG	HILO			AMHD			ROLL		
	FX	GMM	MG	FX	GMM	MG	FX	GMM	MG
ILLQ	0.0113	0.0332	0.2007 **	-0.0137	0.0568	-0.0878	0.0103	0.0064	0.0104
	(0.0534)	(0.0456)	(0.0888)	(0.0523)	(0.0581)	(0.1013)	(0.0255)	(0.0295)	(0.0400)
ILLQ2	0.0551	0.0432	-0.1036	-0.0234	-0.0693	0.0010	0.0115	0.0155	0.0190
	(0.0597)	(0.0448)	(0.0955)	(0.0480)	(0.0529)	(0.0843)	(0.0404)	(0.0491)	(0.0609)
TVOL	0.1655 ***	0.0773	0.4691 **	0.1846 ***	0.1241 *	0.4984 ***	0.2111 ***	0.1082 *	0.5416 ***
	(0.0541)	(0.0505)	(0.2239)	(0.0395)	(0.0658)	(0.1775)	(0.0486)	(0.0583)	(0.1713)
MCAP	-0.0559 ***	-0.0346 ***	-0.0837 *	-0.0784 ***	-0.0508 ***	-0.1644 ***	-0.0778 ***	-0.0538 ***	-0.1473 ***
	(0.0119)	(0.0111)	(0.0449)	(0.0136)	(0.0123)	(0.0416)	(0.0121)	(0.0119)	(0.0407)
PB	-0.0746 **	-0.0786 ***	-0.1017 ***	-0.0604 **	-0.0670 **	-0.1165 ***	-0.0609 **	-0.0702 **	-0.1041 ***
	(0.0281)	(0.0259)	(0.0380)	(0.0277)	(0.0262)	(0.0263)	(0.0280)	(0.0270)	(0.0331)
CF	0.0056	0.0119	0.0334	0.0090	0.0151	0.0385	0.0081	0.0143	0.0364
	(0.0131)	(0.0140)	(0.0450)	(0.0140)	(0.0146)	(0.0410)	(0.0129)	(0.0134)	(0.0420)
MEAN	-0.0802 ***	-0.0737 ***	-0.0768 ***	-0.0976 ***	-0.1073 ***	-0.0827 ***	-0.1020 ***	-0.1026 ***	-0.1052 ***
	(0.0158)	(0.0114)	(0.0156)	(0.0174)	(0.0135)	(0.0230)	(0.0163)	(0.0098)	(0.0163)
|MEAN|	-0.0206	-0.0224	-0.0306 **	0.0082	-0.0160	0.0452	-0.0105	-0.0106	-0.0304 **
	(0.0120)	(0.0132)	(0.0127)	(0.0137)	(0.0193)	(0.0437)	(0.0104)	(0.0101)	(0.0136)
SKEW	-0.0607 ***	-0.0382 **	-0.0916 ***	-0.0587 ***	-0.0210	-0.0904 ***	-0.0590 ***	-0.0248	-0.0599 ***
	(0.0165)	(0.0166)	(0.0236)	(0.0172)	(0.0157)	(0.0263)	(0.0169)	(0.0163)	(0.0216)
PD(-1)	0.1621 ***	0.1992 ***	0.1084 ***	0.1715 ***	0.1920 ***	0.1211 ***	0.1711 ***	0.1935 ***	0.1247 ***
	(0.0147)	(0.0267)	(0.0158)	(0.0160)	(0.0277)	(0.0178)	(0.0162)	(0.0265)	(0.0178)
N	2947	2947	2931	2947	2947	2931	2947	2947	2931
F	54.21	33.91	5.62	63.96	49.18	5.51	82.82	30.50	5.39

Notes: ILLQ is illiquidity according to the high-low spread (HILO), the Amihud measure (AMHD), and the Roll spread (ROLL), respectively. TVOL, MCAP, PB, and CF are trading volume, market capitalization, price-to-book ratio, and cash flow per share, respectively. MEAN is average return, SKEW is skewness, and PD(-1) is the lagged value of predictability. All figures in italic are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. In GMM, our test results do not reject the null hypothesis (H_0) in the AR(2) and Hansen tests but reject it in the AR(1) test at the 1% level.

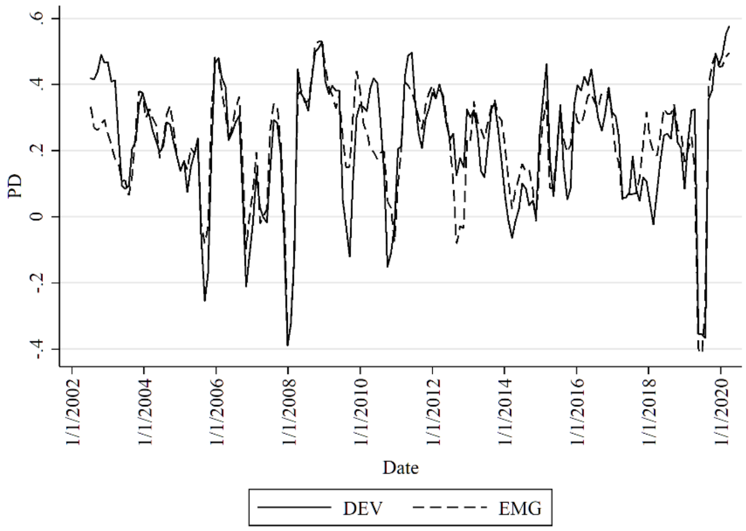

Fig. 1. Predictability over time.

Note: This figure shows the change in predictability as the averages of developed (DEV) and emerging (EMG) markets. Each datapoint represents the predictability measured in the subsequent one-year window.

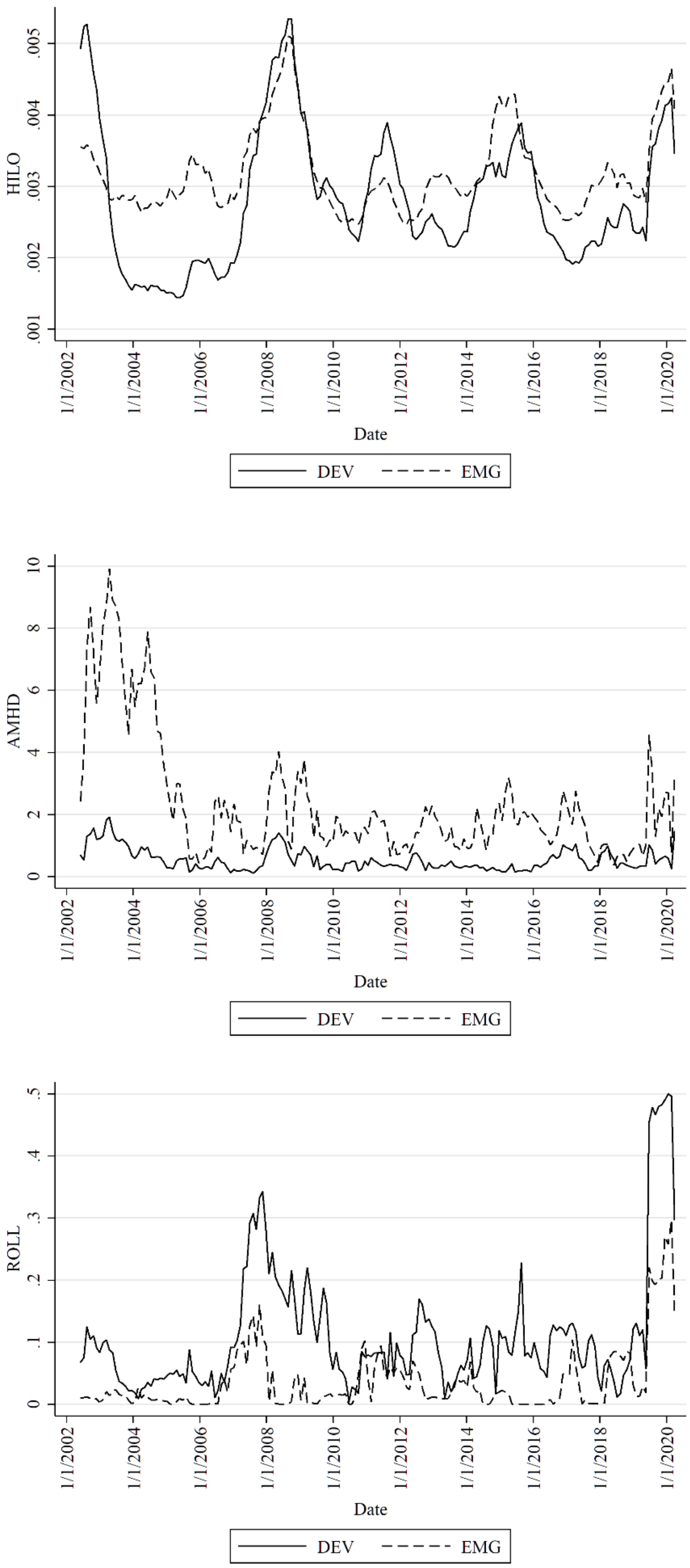

Fig. 2. Illiquidity over time: HILO, AMHD, and ROLL.

Appendix

Table A1

Performance of forecasting models.

S/C	Forecasting Methods		PD	SD	RK
Single	ARMA		0.2201	0.3457	11
	BRK		0.2216	0.3425	7
	ES		0.0840	0.7125	16
Combination	Median		0.2251	0.3412	1
	Mean		0.2054	0.3524	14
	MSE	ARMA-AVG	0.2249	0.3415	2
		BRK-AVG	0.2247	0.3411	4
		ES-AVG	0.2131	0.3456	12
		ARMA-BRK	0.1690	0.4279	15
		ARMA-ES	0.2126	0.3459	13
		BRK-ES	0.2249	0.3412	3
		ARMA-ES-AVG	0.2208	0.3426	9
		BRK-ES-AVG	0.2206	0.3424	10
	Rank		0.2210	0.3409	8
	IC	AIC	0.2247	0.3412	5
		BIC	0.2246	0.3412	6

Notes: This table shows the performance of the single and combined forecasting models on all tests. BRK is AR(1) with breakpoints. ES is exponential smoothing. AVG is the historical average. SD is standard deviation, and RK is ranking in terms of predictability (PD) against naïve forecasts.