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Research

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Time-Series Predictability for Sector Investing

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This study identifies the indicators of sector-level time-series predictability. The results show that investors can expect higher predictability in the more volatile sectors. In the developed markets, price downtrends, lower trading volume, and higher dividend yields indicate stronger predictability. The cyclical and sensitive super-sectors become more predictable as liquidity goes down. Particularly in the cyclical super-sectors, smaller market capitalization and larger term spread also indicate predictability. Sector selection based on the indicators can generate economic benefits.

Keywords: forecasting accuracy; industry selection; return predictability

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Introduction

In the investment process, identifying economic sectors and industries that are expected to gain more than the overall markets is of great importance (Beller, Kling, and Levinson 1998). Investors may go further by choosing individual securities but may simply hold industry portfolios, funds, or sector exchange-traded funds. This investing strategy, generally known as "sector investing," seeks a balance between passive index investing and active stock selection (Alexiou and Tyagi 2020). Sector investing is not only about selecting the best industry in which to invest but also about rotating sectors based on geographical locations or business cycles. It requires industry analysis, which has many aspects, such as examining fundamentals and the industry's environment. Often ignored, however, is how well investors can predict future stock returns in a specific industry sector.

One of the predictors, which has been widely tested and is among the simplest, is stock price itself—specifically, past and current returns. The existence of this time-series predictability has been strongly supported by studies of financial markets in the past few decades (Yen and Lee 2008; Lim and Brooks 2011) as has rejection of the weak form of market efficiency (e.g., Narayan and Smyth 2015; Fama 1991). Time-series predictability fits many behavioral and rational pricing theories that are based on a single risky asset (Moskowitz, Ooi, and Pedersen 2012). Predictability that uses all nonprice public information is often denoted "cross-sectional predictability" (McLean and Pontiff 2016). Several factors have been tested for their predictive power, with financial ratios, such as dividend yield and the price-to-earnings ratio, being among the most commonly tested (Rapach, Strauss, and Zhou 2010; Campbell and Thompson 2008; Welch and Goyal 2008; Campbell and Shiller 1988). And some researchers have tested combinations of predictors to extract more information than is available from only a single predictor (Dai and Zhu 2020; Zhang et al. 2019; Jordan, Vivian, and Wohar 2014; Timmermann 2006).

Sector-level analysis of predictability, however, is often overlooked even in the more common studies of cross-sectional predictability.

Yet, sector-level predictability can be stronger than market-level predictability (Bannigidadmath and Narayan 2016) and can differ across industry sectors; that is, some sectors are more predictable than others (Phan, Sharma, and Narayan 2015). The reason could be that investors receive more valuable pricing information in certain industries or that information possession and processing are heterogeneous across industries (Bannigidadmath and Narayan 2016; Westerlund and Narayan 2015a).

Sector-level predictability is important because, in practice, investors do not hold well-diversified portfolios. Household investors tend to hold undiversified portfolios that target a few industries, not only because of behavioral biases but also because of financial constraints and limited borrowing opportunities (Roche, Tompaidis, and Yang 2013). Mutual funds also hold portfolios concentrated in industries when they believe certain sectors will outperform or the funds have superior information about specific industries (Kacperczyk, Sialm, and Zheng 2005). Narayan, Ahmed, and Narayan (2017) show that investors will benefit greatly from investing in certain sectors—such as technology and financials in the United States. Also, fund managers' industry selection skills are known to drive their relative performance (Busse and Tong 2012), and funds that are more industry-concentrated perform better than less concentrated ones (Kacperczyk, Sialm, and Zheng 2005). As for portfolio diversification, seeking diversification across global sectors is important when global markets tend to be integrated (Cavaglia, Brightman, and Aked 2000). Industry-wide categorization is also known to influence the investment decisions of retail investors and thus affect stock prices (Jame and Tong 2014).

If investors who pursue sector investing want to identify sectors where they can best predict future returns, they need to understand how certain industry factors or characteristics are associated with sector-level predictability. For example, Westerlund and Narayan (2015a) show that relative valuation measures, such as the book-to-market ratio, can explain sector-level predictability. Risk premiums can also vary at the sector level, as seen in the studies using the Fama–French three-factor model (Rapach et al. 2011) and the capital asset pricing model (Narayan and Bannigidadmath 2015).

Understanding sector-level predictability is not an easy task, however, when return predictability is expected to be time-varying. Finding predictors and models that can improve on even the most naive benchmark forecasting models in out-of-sample periods is difficult (Welch and Goyal 2008) because the degree of market efficiency is known to change over time (Lim and Brooks 2011). Investors' behavior responds to varying market conditions too (Lo 2004). Risk factors in pricing models could vary with the business cycle because risk-averse investors could demand higher risk premiums during crisis periods (Guiso, Sapienza, and Zingales 2018; Fama and French 1989; Campbell and Cochrane 1999).

Most past studies of time-varying predictability examine cross-sectional predictability and determinants, such as financial ratios (Bannigidadmath and Narayan 2016; Kim, Shamsuddin, and Lim 2011; Timmermann 2008; Paye and Timmermann 2006). The time variability of time-series predictability, however, is rarely investigated. Time-series predictability is usually assumed to be unchanged in the weak-form efficiency literature, but Moskowitz, Ooi, and Pedersen (2012) emphasize the importance of time-series predictability. They also highlight that cross-sectional and time-series predictability are related and that the underlying driver of the changes is time-series predictability. Some studies trace the time variability of time-series predictability to market-level factors (Lim and Brooks 2011; Lagoarde-Segot 2009) but not to sector-level factors.

Therefore, our study has three main objectives. First, we investigate whether time-series predictability exists and how it differs across industry sectors and over time. Next, we examine which sector-level characteristics can indicate the degree of time-series predictability. Note that the indicators of time-series predictability are not the same as the predictors of returns. Indicators of time-series predictability signify the degree to which future stock returns can be forecasted by past and current returns, but predictors of returns attempt to predict future stock returns. Finally, we evaluate the economic significance of time-series predictability for investment management, particularly for sector investing, in the form of gains in predictability and investment returns.

Many studies have not considered the type of investors who benefit from predictability. Investors are commonly assumed to have access to a large amount of public information and thus to be able to exploit cross-sectional predictability. In reality, few investors seem to be capable of taking advantage of this predictability (Cooper and Gulen 2006) despite academic evidence of exploitation (McLean and Pontiff 2016). Also, certain types of investor may need to, or be willing to, pursue time-series predictability instead of cross-sectional predictability.

In this regard, our study focuses on the type of investor who, unlike the rational investor of classical finance, does not use full information. Following Barberis and Thaler (2005), we call these investors "less rational investors," but because Barberis and Thaler find many possible departures from rationality, a further simplifying choice is required to make the subsequent analysis manageable. Therefore, we assume that less rational investors use only past price history for forecasting but know certain contemporaneous sector fundamentals for sector selection. In addition, they do their best by combining the forecasts from univariate models and updating their models under changing market circumstances, similar to those in Lo's (2004) adaptive markets hypothesis. The benefit of adopting less rational investors for this study is that the predictability of their forecasting models will tend to be conservative and not be overstated because of the limited information. Also, our findings can be generalized to more rational or "able" investors.

In essence, this study aims to identify the indicators of sector-level time-series predictability for less rational investors' sector investing. We use a two-step approach inspired by the multistep methods of Phan, Sharma, and Narayan (2015), Wang et al. (2018), and Devpura, Narayan, and Sharma (2018). We measure time-series predictability in each sector and then identify the indicators of the times-series predictability by a panel regression model. Our technical approach is distinct from these authors' approaches. The main difference in the first step is that we measure predictability by less rational investors' best forecasting accuracy in terms of out-of-sample forecasting errors, instead of examining the direct link between returns and one-step backward predictors commonly found in the studies of cross-sectional predictability. Therefore, we essentially are studying out-of-sample predictability, an idea shared with Kong et al. (2011). We can more easily propose a practical approach that would help investors where in-sample evidence is irrelevant (Rapach et al. 2011; Welch and Goyal 2008). In the second step, we analyze the dynamic panels of sector-level indicators and predictivity rather than testing each predictor in a time-series setup (Devpura, Narayan, and Sharma 2018; Phan, Sharma, and Narayan 2015) or building component portfolios on indicators (Kong et al. 2011). Specifically, we adopt the dynamic common correlated effects estimator. It controls for cross-sectional dependence, which potentially exists across sectors and markets, while fully using long time series and large cross-sections.

We explore two more dimensions—market development and super-sectors. On the one hand, the emerging markets are expected to be more predictable than the developed markets (Harvey 1995) because of lower liquidity (Acharya and Pedersen 2005) and less established market microstructures, such as a lack of trading system automation, insider trading regulations, and accounting standardization (Lagoarde-Segot 2009). On the other hand, they are guided more by heterogeneous local information (Harvey 1995), are less correlated with the global markets (Berger, Pukthuanthong, and Yang 2011; Zaremba et al. 2021), and are often subject to financial reforms. Therefore, predictability in the emerging markets is likely to be more time-varying than in the established markets. Super-sectors, which Morningstar (2010) defines as cyclical, defensive, and sensitive, are classified according to their sensitivity to the business cycle. Return predictability may vary across the super-sectors as the markets ride the business cycle.

Our findings show that sector-level time-series predictability is not strong and was not affected by the COVID-19 pandemic but varies across sectors and market development. Certain indicators can imply stronger time-series predictability for less rational investors. For example, in general, more volatile sectors are more predictable. In the developed markets, price downtrends and lower trading volume but higher dividend yield indicate stronger predictability. The emerging markets do not have such relationships despite their higher level of predictability. Super-sectors, which are sensitive to the business cycles, become more predictable as liquidity decreases. In the cyclical super-sectors, price downtrends, small market size, and larger term spreads also indicate predictability.

Our indicators successfully indicate the existence of sectors with stronger time-series predictability in out-of-sample periods. Exploiting higher predictability for higher profits, however, is not easy. Among the sector-level buy-and-hold strategies we test, we find that those based on market size, illiquidity, and term spread lead to consistently higher returns than the market.

This study makes several important contributions. First, it provides practical and forward-looking indicators for investors who seek predictable sectors. In those sectors, they can potentially generate more profits from their trading strategies than in the other sectors. Second, this study demonstrates a new perspective on measuring predictability. We first theoretically define a type of investor and then adopt their forecasting performance as predictability. Our approach bypasses the potential issue of specifying a certain structure between returns and predictors. Third, we show sector-level heterogeneity in time-series predictability by investigating multiple dimensions: sectors, super-sectors, and stage of market development. As a result, more applications can be devised in sector investing than with market-level investing. Finally, our study examines the impact of the COVID-19 pandemic on time-series predictability. It complements the recent strand of literature on cross-sectional predictability (see, among others, Ciner 2021; Hasan 2022; Ma et al. 2022; Naidu and Ranjeeni 2021; Rahman, Amin, and Al Mamun 2021; Salisu and Vo 2020).

Methods

In this section, we discuss how we measure time-series predictability, identify the indicators of such predictability, select candidate indicators, and test for the economic significance of sector-level predictability.

Measuring Time-Series Predictability. We measure time-series predictability by the forecasting performance of less rational investors on a rolling-window basis. The rolling-window method is a popular method of examining the evolution of market efficiency. According to a survey paper by Lim and Brooks (2011), there are three research frameworks for dealing with time-varying market efficiency or predictability: subperiod analysis, time-varying parameter models, and rolling estimation windows. First, we do not use subperiod analysis because it assumes that the model parameters change at only a few predetermined points. In other words, it cannot provide a sufficient number of observations to model the time variability of predictability. In contrast, the time-varying parameter model allows the model parameters to change through time and thus captures the changes in predictability. However, it requires a strong assumption about how returns are generated or related to the predictors, such as state–space or autoregressive models (see, e.g., Dangl and Halling 2012). Our approach of measuring predictability by forecasting accuracy via rolling windows does not require either return generation processes or forecasting models to be always correct.

In our method, each rolling window is approximately one year long: 250 trading days. The investors observe daily stock returns in the previous 200 days (the estimation period) and then produce daily forecasts by using multiple forecasting models. They use the intermediate 25 days (the training period) to calculate the weights for combining forecasts where necessary and then forecast future returns for the next 25 days. These last 25 days (the evaluation period) are used to evaluate forecasting errors and performance. The accuracy of the best forecasts in each rolling window is converted to one corresponding value of time-series predictability. The sizes of these periods are inspired by Moskowitz, Ooi, and Pedersen (2012), who find that a relationship between lagged one-year returns and the following month's returns is the dominant force behind time-series predictability.

Then, we move the rolling window by 25 days, about one calendar month, and repeat the process until we obtain a monthly series of time-series predictability. We repeat the process for each sample sector and market. Eventually, we have panel data on monthly predictability.

We prefer the rolling-window method to the alternative expanding (or recursive) window method because the rolling-window method better represents less rational investors' use of limited information.

Note that estimation periods partially overlap. Overlapping observations can incorporate more information and lower the variance of estimates but potentially incur autocorrelation, which we later control for in a dynamic panel model.

The less rational traders are assumed to choose three forecasting models: naive, exponential smoothing, and autoregressive moving average (ARMA). Rather than testing a large number of forecasting models, we adopt these three simple models, which are widely used but incorporate only past prices. Therefore, if we measure their forecasting accuracy as predictability, the level of predictability ought to be conservative and not overstated. Also, this level can be considered a minimum level of predictability for more rational or able investors.

In detail, first, the naive model uses the historical average of returns in the estimation period as the future forecast. It is also used as a benchmark for calculating forecasting performance. Second, the simple exponential smoothing model (Gardner and Mckenzie 1985) predicts the future returns as the weighted average of the current return and the immediate-past forecast. The weights are estimated to minimize the Schwarz information criterion (SIC). Finally, the ARMA models use the past values of returns and the contemporaneous and past errors to predict future returns. Specifically, we choose the best AR and MA orders based on the SIC after testing up to three lags.

Single forecasts from these three models are additionally merged into combined forecasts, which are known to perform better and be less variable than single forecasts (Hibon and Evgeniou 2005). We use six combination methods. Except for the median method, they calculate the weighted average of three single forecasts ($\sum_{i=1}^{3} w_i r_i^f$), where w_i is the weight of single forecast i (r_i^f). The mean method (the first method) and the median methods (second) calculate the average and the median of three forecasts, respectively. They often outperform more complicated methods (Clemen 1989). The least-squares method (third), which was popularized by Granger and Ramanathan (1984), finds the w_i that minimizes the forecast errors in the training period. The rank method (fourth) of Aiolfi and Timmermann (2006) evaluates the performance of single forecasts in the training period and calculates w_i by the performance rank (ρ_i) as $w_i = \rho_i^{-1}/\sum_{j=1}^{3} \rho_j^{-1}$. The Akaike (fifth) and the Bayesian (sixth) information criterion methods calculate w_i from the values of information criterion (C) as $w_i = \exp(-1/2C_i)/\sum_{j=1}^{3}(-1/2C_j)$.

The predictability in each rolling window τ (PD_τ) is measured as the largest reduction of forecasting errors relative to those by the naive model. In other words, PD represents the best forecasting accuracy among the single and combined forecasting models:

$$PD_\tau = \max_m (1 - M_{m,\tau}/M_{v,\tau}), \qquad (1)$$

where M is the root mean squared error of forecasted returns over actual returns and m is single or combined forecasting models except the naive (v) model. This measure is essentially similar to finding the model with the largest out-of-sample R^2 (Campbell and Thompson 2008; Henkel, Martin, and Nardari 2011) among candidate forecasting models. In addition, the statistical significance of predictability is evaluated against the naive model following the tests by Clark and West (2007) and Zhang et al. (2019). Note that we do not adopt Westerlund and Narayan's (2015a, 2015b) method or its extension (Devpura, Narayan, and Sharma 2018) despite the methods' growing popularity in testing cross-sectional predictability. Our study uses a different definition of predictability based on out-of-sample forecasting. Also, their methods essentially use a bivariate model between a return and a nonprice predictor and thus are not easily used to test the time-series predictability of return, which is of a univariate nature.

Identifying the Indicators of Time-Series Predictability. Finally, we bring together the individual series of PD generated for each sector into a dynamic panel. Then, we identify the indicators for sector-level time-series predictability. Technically, we estimate how the values of individual indicators in the estimation periods are associated with the predictability in the evaluation periods of the rolling windows. We adopt two dynamic panel models: the dynamic fixed effects (FE) model and the dynamic common correlated effects (DCCE) model.

Our first model is the dynamic FE model with autoregressive terms of PD:

$$PD_{s,\tau} = \alpha_s + \beta x_{s,\tau} + \gamma' \boldsymbol{PD}_{s,\tau-l} + e_{s,\tau}, \qquad (2)$$

where s is a sector, α is a cross-section fixed effect, x is an indicator of predictability, β is its coefficient, γ is a vector of coefficients for lagged PDs, and e is the error term.

We add eight lagged values of PD ($l = 1, \ldots, 8$) to account for the correlation that may be caused by overlapping estimation periods in the rolling-window method. The values of the indicators for each rolling window τ in sector s ($x_{s,\tau}$) are calculated as the average values within the corresponding estimation period and the sector. We test each indicator individually, which is a common approach in studies of return predictors.

Despite their wide use, FE models allow only the intercepts to differ across the cross-section groups (Blackburne and Frank 2007) and assume all other coefficients and error variances are the same (Pesaran, Shin, and Smith 1999). Furthermore, the dynamic FE estimator with the lagged dependent variable is known to be subject to a downward bias, particularly in samples with a small number of observations (T) over time (Pesaran, Shin, and Smith 1999), although the impact of that characteristic should be minimal in our sample because it has a fairly large T.

Therefore, we use the DCCE estimator, which allows for heterogeneous parameters across cross-sections. The DCCE estimators (Chudik and Pesaran 2015) further account for unobserved common factors between cross-sections, which can generate cross-sectional dependence, by including both contemporaneous and lagged cross-section averages. This characteristic is especially important in sector-level international studies, where cross-sectional dependence can occur within local markets as well as across the same sectors and the related super-sectors in the global markets. The DCCE estimator is given by

$$PD_{s,\tau} = \alpha_s + \beta x_{s,\tau} + \gamma_s' \boldsymbol{PD}_{s,\tau-l} + \delta_s' \boldsymbol{f}_\tau + e_{s,\tau}, \quad (3)$$

where $\boldsymbol{f}$ is a vector of unobserved common factors, $\boldsymbol{\delta}$ is a vector of heterogeneous factor-loading, and $\boldsymbol{\Omega}$ is the variance–covariance matrix. In particular, the DCCE specifies $\delta_s' \boldsymbol{f}_\tau = \sum_{l=1}^{p} \boldsymbol{\eta}_{s,l}' \bar{\boldsymbol{z}}_{\tau-l}$, where $\bar{z} = (\bar{y}_{\tau-1}, \bar{x}_\tau)$. The sample estimates of β and γ are obtained as cross-sectional averages. The number of cross-sectional lags is calculated as $T^{(1/3)}$, following Chudik and Pesaran (2015) and Ditzen (2018). We additionally adopt recursive mean adjustment (see So and Shin 1999) for potentially autocorrelated data.

Selecting Candidate Indicators. The selection of the indicator variables is driven by the literature on cross-sectional predictability. If time-series and cross-sectional predictabilities are related (Moskowitz, Ooi, and Pedersen 2012), those variables may affect time-series predictability. On the one hand, the earlier literature (e.g., Fama and French 1988) applied the dividend discount model and tested dividend yield for cross-sectional predictability. Wang et al. (2018) tested 12 macroeconomic variables and confirmed that dividend yield has particularly strong predictive power, whereas most of the others have little predictive power. Recent studies by Zhu (2015) and Hammami and Zhu (2020) also emphasize the importance of dividend yield.

On the other hand, several studies have adopted Campbell and Thompson's (2008) framework to examine a variety of single predictors (e.g., Westerlund, Narayan, and Zheng 2015; Westerlund and Narayan 2012; Phan, Sharma, and Narayan 2015; Rapach, Strauss, and Zhou 2010). Their results show that company fundamentals, market valuation, and trading activities can affect return predictability. For example, Phan, Sharma, and Narayan (2015) find that a higher book-to-market ratio (B/M) and larger trading volume increase return predictability while a higher price-to-earnings ratio (P/E) and larger firm size decrease it. Similarly, Kong et al. (2011) show that return predictability is stronger for small-cap stocks or those with a higher B/M. Chen, Firth, and Rui (2001) highlight the role of trading volume. Liquidity and transaction costs can influence investment decisions too because they can obstruct the execution of any investment strategies. Similarly, wide bid–ask spreads increase stock predictability (see Chordia, Roll, and Subrahmanyam 2008; Chung and Hrazdil 2010a, 2010b). The return–illiquidity relationship (or illiquidity premium) can also be linked to predictability (see Amihud 2002; Amihud et al. 2015). Built on Welch and Goyal (2008), Devpura, Narayan, and Sharma (2018) conclude that P/E and stock volatility can explain the predictability. Government bond yields and term spreads are also often tested for a relationship with return predictability (see, e.g., Rapach, Ringgenberg, and Zhou 2016).

We, therefore, use the following sector-level factors as the indicators of predictability: dividend yield, P/E, book-to-price ratio (B/P), return on equity (ROE), dollar trading volume, market capitalization, illiquidity, and market/sector excess returns. In addition, we include a dummy for negative price trends and standard deviation for the general risk level. A dummy for business cycles is also adopted. As macroeconomic variables, we use short-term government bond yields (short rates) and term spreads. However, we do not use the factors related to corporate bonds and corporate issuing activity as in Wang et al. (2018) and Welch and Goyal (2008) because of a lack of consistent data for the study of international markets and sector-level analysis.

Our expectation is as follows. The valuation of stocks relative to fundamentals is known to influence predictability (Kong et al. 2011; Phan, Sharma, and Narayan 2015). On the one hand, lower valuation increases predictability (Kong et al. 2011) because highly valued stocks may be subject to sudden correction. We expect dividend yield, P/E, and B/P to behave similarly. We also test ROE, as operating performance, for comparison. On the other hand, trading volume can represent the magnitude of information flow (Chen, Firth, and Rui 2001). Large volumes may be a consequence of either excessive noise or relevant information, which can hinder or support predictability (Phan, Sharma, and Narayan 2015). Market capitalization may work similarly but can also represent market development, in the sense of markets becoming more efficient and less predictable.

Stock volatility may reflect excessive information arrival and make traders less successful in information processing and model estimation (Chung and Hrazdil 2010b; Timmermann 1993), but this uncertainty can create underpricing (Timmermann 1993, 1996), which may generate predictable price movement. Illiquidity hinders arbitrageurs' ability to correct mispricing quickly (Chung and Hrazdil 2010a;

Chordia, Roll, and Subrahmanyam 2008) and thus may increase predictability.

Sectoral excess return as industry stock price performance is linked to business cycles; stock return predictability is known to be higher in an economic downturn (Henkel, Martin, and Nardari 2011; Kim, Shamsuddin, and Lim 2011). This effect could be even stronger during negative sector performance and contraction in the business cycle (Guiso, Sapienza, and Zingales 2018; Fama and French 1989; Campbell and Cochrane 1999). Short-term government bond yields (or short rates), a common proxy for risk-free rates, may reflect monetary policies reacting to the business cycle. Similarly, term spreads are expected to work as an indicator of the business cycle. That is, low short rates and negative or low term spreads may be connected to higher predictability.

These indicators are roughly categorized as follows: price and trade originated (negative price trend, volatility, trading volume, market capitalization, illiquidity, and excess return), relative valuation (dividend yield, P/E, and B/P), operating performance (ROE), or macroeconomic (business cycle, short rates, and term spreads).

Testing Economic Significance. Knowing the indicators of sector-level predictability can help investors make decisions, but demonstrating that this knowledge can indeed provide economic significance is imperative. For example, regarding cross-sectional predictability, Narayan, Ahmed, and Narayan (2017) show that the gains in investing in certain sectors based on nonprice predictors are substantial. The authors pay little attention, however, to the indicators of time-series predictability. Therefore, this study, first of all, investigates whether the sectors selected on the basis of the identified indicators provide stronger time-series predictability than the other sectors, both in the in-sample and the out-of-sample periods. In addition, stronger predictability needs to eventually turn into stronger economic benefits for investors. Therefore, we also examine whether economic significance is easily achievable from trading strategies built on our indicators. Like Balvers, Wu, and Gilliland (2000) and Narayan, Liu, et al. (2016), a common framework is to compare the returns from the trading strategies with the return of a buy-and-hold benchmark strategy. However, even though investors know the indicators of strong sector-level predictability, they can adopt numerous trading strategies. Therefore, as demonstrations, we test a small number of simple time-series–based strategies: strategies that require minimal effort and thus are suitable for less rational traders. If these simple strategies can outperform benchmarks, more-capable investors could do better with sophisticated strategies. Note that we do not adopt utility gains, as in Narayan, Hoang et al. (2016), for example, because this measure cannot easily capture gains when investors choose more volatile sector investing over market portfolios.

We assume the investors know which sectors they need to choose following the indicators identified in this study. Their investment horizon is also rolling-window–based as specified previously. Specifically, after the estimation period of each rolling window, the investors select the top 10 sectors based on each indicator—for example, the top 10 least liquid sectors in cyclical super-sectors. Then, they use one of the three sector-level buy-and-hold strategies and hold the portfolios over the evaluation period. We calculate their investment returns and compare them with the market buy-and-hold strategy. The trading costs involving the indicator-based buy-and-hold strategies should be comparable to the market buy-and-hold strategies.

The investors' trading strategies are as follows. First, the investors find which forecasting model works best in the previous rolling window and go long or short the stocks on the basis of its prediction for the current evaluation period. They trade only in the selected top 10 sectors in the expectation that their forecasting model will perform better in those sectors. Second, the investors adopt the naive forecasting model and go long or short the stocks on the basis of its prediction—that is, the average historical return in the estimation window. In this approach, the strategy is also a momentum strategy. Again, expecting higher predictability for those sectors, the investors trade those top 10 sectors. Finally, even more naively believing that predictability will turn into profitability in the top 10 sectors, the investors simply buy and hold those sectors. This last approach can be said to be a buy-and-hold strategy in sector investing, and the earlier two strategies are its variants with forecasting elements.

Data

The sample data cover 47 international stock markets from 2 January 1999 to 30 June 2022 (see Table 1). For each market, one market-wide index and 11 industry-sector indices are used. The number of daily observations is 6,310 for each return series and

Table 1. Summary Statistics I: Market Averages

Market		SD	TV	MC	IL	PF	DY	P/E	B/P	ROE	RF	TS
DEV	Australia	1.4368	12.2172	11.0697	0.1282	0.0145	3.9107	27.1151	2.7109	11.6846	1.3448	2.0078
	Germany	1.5036	8.6642	11.5517	1.1984	0.0056	2.5475	24.0023	2.1309	8.7253	1.1627	1.1928
	Belgium	1.4304	9.4656	9.2676	0.9584	0.0137	2.9379	20.9906	2.0673	11.1665	0.6988	1.5598
	Canada	1.4532	12.1328	11.1914	0.1030	0.0172	2.4511	31.7803	2.4662	9.3802	1.9005	1.2828
	Denmark	1.9411	9.1403	8.5353	1.6512	0.0278	1.9692	31.1459	3.3433	16.0636	1.4412	1.1566
	Spain	1.5578	11.2802	10.3980	0.2434	−0.0017	3.5336	28.8956	2.5031	9.9258	0.1863	2.3186
	Finland	1.8097	10.2518	9.2587	0.7011	0.0203	4.0156	23.4057	2.3882	13.8753	1.4252	1.1391
	France	1.5275	12.7788	11.7930	0.0546	0.0090	3.4210	20.9369	2.0425	9.3189	1.2477	1.4678
	Hong Kong	1.6373	11.7674	11.1342	0.3382	0.0202	2.6221	18.2473	2.5070	13.5017	1.3514	1.6929
	Ireland	2.5025	7.3979	7.7859	3.2054	−0.0040	1.1762	34.7630	3.0136	1.0067	−0.3593	0.8027
	Israel	1.6908	9.0071	8.8133	1.2577	0.0236	3.4071	30.6176	2.2465	11.0741	15.4078	−8.1377
	Italy	1.6467	11.6280	10.3020	0.2995	−0.0015	2.9409	31.2378	1.8219	8.5631	1.5197	2.1067
	Japan	1.4503	13.9150	12.6034	0.0205	0.0022	1.8110	30.4579	1.5362	6.4108	0.0611	0.8328
	Netherlands	1.8297	11.2454	10.1206	0.6413	0.0032	2.7993	25.9618	2.5897	8.8105	−0.2697	1.2484
	Norway	1.9274	10.0624	9.2906	0.8708	0.0178	3.0545	26.1123	2.0534	12.2992	2.6344	0.7007
	New Zealand	1.4172	7.9517	7.8391	1.7801	0.0223	4.2189	22.4998	2.1302	11.3797	3.9995	0.5051
	Portugal	1.9353	7.1734	7.3315	2.7261	−0.0155	4.3811	26.2359	1.3812	5.8789	0.0082	2.7556
	Sweden	1.8403	11.5272	10.2382	0.2381	0.0262	2.6663	28.1847	3.0594	15.8505	1.4552	1.2398
	Singapore	1.5015	9.6125	9.2674	1.1353	0.0085	2.6664	21.3865	1.6933	11.7643	1.0630	1.5105
	Switzerland	1.3537	11.5154	10.7396	0.3436	0.0152	2.2025	20.1869	2.5587	13.6684	0.4594	1.0261
	UK	1.4552	13.3120	12.1079	0.0324	0.0020	3.4355	18.8349	2.7906	14.2432	2.2764	0.8426
	US	1.2610	15.8708	14.0200	0.0023	0.0153	2.4847	22.7589	3.1149	13.9803	1.6120	1.6761
EMG	Brazil	2.1600	11.7595	10.6165	0.2678	0.0000	3.4436	25.4647	2.4559	11.7026	9.6105	1.4147
	China A	1.7988	14.0699	12.2144	0.0268	0.0237	1.5976	28.5100	2.8893	12.6271	3.1650	0.3545
	China B	2.0011	11.7847	10.0369	0.2602	0.0102	2.4952	18.6359	1.9771	11.5828	3.2101	0.2913
	Chile	1.6086	8.7303	9.1395	1.2541	−0.0150	2.9164	25.8102	1.9073	10.1293	4.5832	0.3466
	Czech	1.4833	6.5719	7.3896	2.9716	0.0067	4.3426	20.8728	1.8978	14.1406	0.1180	1.9921
	Greece	2.3451	7.6521	7.8136	2.3473	−0.0185	2.3171	21.8746	1.1823	1.9536	3.3439	3.8690
	Hungary	2.3083	6.9775	6.8988	2.0313	0.0066	3.2597	27.0248	1.8169	10.6807	5.5000	0.6441
	India	1.7266	11.2712	11.0336	0.3051	0.0351	1.5768	23.7828	3.2264	17.0334	6.3024	1.0671
	South Korea	2.7272	12.1815	10.6485	0.1537	0.0193	1.9634	23.0006	1.4130	9.8267	3.2358	0.7920
	Mexico	1.6931	10.3210	10.1182	0.6389	0.0085	2.1616	20.1079	2.4280	12.3317	5.0802	1.6038
	Malaysia	1.1835	9.5784	9.5319	0.6905	0.0189	2.9188	18.3669	2.0044	11.9652	2.9064	1.0005
	Peru	1.4675	5.8973	8.0942	3.6566	−0.0137	3.6918	20.2083	1.7975	13.0065	3.5252	1.6044
	Philippines	1.7626	8.3292	8.8882	1.4950	0.0198	1.9726	22.8421	2.3277	13.7424	3.8207	3.2765
	Pakistan	1.6033	8.1796	7.8596	1.5966	0.0003	5.2379	15.6491	2.6984	20.6600	9.2444	1.7282
	Poland	1.9058	8.9971	8.7964	1.2893	0.0007	3.0981	21.4273	2.7130	14.7668	2.5856	1.1346
	Russia	2.3132	9.3416	9.7583	1.5089	0.0082	2.8518	14.5517	2.1183	16.6844	7.8617	0.4571
	South Africa	1.9899	11.2838	10.3488	0.2221	−0.0006	3.6744	17.5220	2.5456	17.2897	6.0362	2.3918
	Taiwan	1.5398	11.3104	10.3349	0.3094	0.0248	3.6432	22.1451	2.0853	12.4826	0.9161	0.6470
	Thailand	1.7811	9.7408	9.0119	0.9194	0.0241	3.4603	19.3888	2.7204	15.9911	2.7661	0.8821
	Turkey	2.1763	10.8519	9.2808	0.4788	−0.0199	3.3937	13.9983	1.5959	13.8889	10.6043	0.6014
FRT	Bulgaria	1.6069	3.6554	5.6322	6.2313	0.0045	2.4708	22.3883	1.4204	7.9773	0.7579	1.8669
	Cyprus	1.2466	2.6879	5.0915	6.5243	0.0053	2.2826	24.1108	0.8604	4.0594	1.7573	0.3942
	Sri Lanka	1.6156	4.4645	6.2111	4.1742	−0.0135	4.1145	18.4692	1.8398	14.2347	7.4379	2.7771
	Romania	2.0857	4.8385	6.3542	4.9380	−0.0041	3.1321	19.3715	1.3713	8.8046	4.7126	1.0149
	Slovenia	1.6864	4.9986	6.6413	4.4534	−0.0280	3.4234	26.0138	0.9627	6.4024	3.7281	−0.7741

Note: This table presents the market averages of sector-level factors. SD is standard deviation representing volatility. TV is (log) dollar trading volume. MC is market value in (log) million US dollars. IL is illiquidity. PF is excess return over the risk-free rate measured as the short-term government bond yield. DY is dividend yield. P/E is the price-to-earnings ratio. B/P is the book-to-price ratio. ROE is return on equity. RF is risk-free rates and TS is term spreads. Markets are classified as developed (DEV), emerging (EMG), and frontier (FRT) markets.

3,273,203 in total. Each daily return series is eventually converted to the predictability series by the rolling-window method as explained in the section on methodology. The number of windows is 236 for each sector and market and 84,692 in total. The first 185 windows in each series, ending on 22 September 2016, are used as the in-sample period (IS) to estimate the model for the indicators of time-series predictability. Then, the remaining 50 windows, between 23 September 2016 and 30 June 2022, are used as the out-of-sample period (OOS). They are equally divided into the pre-pandemic out-of-sample period (OOS1) and the pandemic period (OOS2). Periods OOS1 and OOS2 are divided by the date on which the World Health Organization declared a public health emergency: 31 January 2020. Our main data source for stock prices is the Thomson Datastream Global Equity Indices, which provides a standardized way for comparative studies of international stock markets. The corresponding financial and accounting variables are from Datastream Worldscope and Eikon.

The sector classification follows the Industry Classification Benchmark: energy (ENEG), basic materials (BMAT), industrials (INDU), consumer discretionary (CODI), consumer staples (COST), telecommunication (TELC), technology (TECN), financials (FINA), utilities (UTIL), health care (HLTH), and real estate (RLES). The industry sectors are further categorized into three super-sectors on the basis of their implications for investment strategies (Morningstar 2010): (1) cyclical, which contains BMAT, CODI, FINA, and RLES; (2) sensitive, which contains ENEG, INDU, TELC, and TECN; and (3) defensive, which contains COST, UTIL, and HLTH. *Cyclical* super-sectors are the most pro-cyclical in terms of following business cycles and having high beta risk. *Sensitive* super-sectors are moderately related to business cycles. *Defensive* super-sectors are counter-cyclical and characterized by low beta risk because the stock prices are generally not affected by economic fluctuations (Singh 2020; Makarov and Papanikolaou 2008). The firms in the defensive super-sectors generate revenue during recessions as well as other parts of the business cycle and thus exhibit low volatility.

Using the MSCI Country Classification Standard, we also classify the sample sectors into three subgroups based on market development, namely, developed (DEV), emerging (EMG), and frontier (FRT). The frontier markets are only included in the full sample analysis, not the subsample analysis, because of their small sample size.

The indicators of predictability are measured as their average values in the estimation period in each rolling window. Specifically, a general risk level is measured by the standard deviation of return. Market capitalization is represented by the total value of ordinary shares of all index constituents, in millions of US dollars. Dollar trading volume or turnover by volume (TV) is the aggregation of the number of shares traded multiplied by the closing price, in thousands of US dollars. Illiquidity (IL) is measured following Amihud's (2002) illiquidity measure: the absolute return divided by dollar trading volume plus 1. Stock performance (PF) is proxied by stock index returns less risk-free rates. DY, P/E, ROE, and B/P are weighted by the market values of the constituents. Following the business cycle dating of the National Bureau of Economic Research, the business cycle (BC) indicator has a value of 1 in expansion and 0 in contraction. Short rates representing risk-free rates are proxied by short-term (3-month) government bond yields. For the countries without these data, we adopt the next shortest term government bond yield (1 or 2 years). Term spreads (TS) are the gap in yields between long-term (10-year) government bonds and RF. The correlations of these indicators are presented in Table 2. The variables are winsorized at 1 and 99% to minimize the impact of outliers and normalized for regression.

Results and Discussion

Time-series predictability exists in about 14% of the rolling windows of all tested sectors (Table 3, Panel A). Considering that the predictability can arise in about 5% of them by chance, this finding confirms a significant level of predictability despite earlier findings that once variability is considered, predictability might appear only sporadically (Timmermann 2008). The average value of measured predictability (PD) is around 0.013 (1.3%), which essentially quantifies the less rational investors' forecasting performance over naive forecasting (Table 3, Panel B).

A certain level of cross-sectional variation of time-series predictability is observed across sectors (as shown in Panels A and B of Table 3). For example, the cyclical super-sectors are relatively more predictable than the other super-sectors. The financial, real estate, industrial, and technology sectors exhibit strong predictability. This sector-level heterogeneity is consistent with Kong et al. (2011), but its size is small. The emerging and frontier markets are more predictable than the developed markets (Panel B of Table 3). Panel C of Table 3 clearly shows that

Table 2. Summary Statistics II: Correlations

	SD	TV	MC	IL	PF	DY	P/E	/BP	ROE	RF	TS
SD	1										
TV	−0.1375	1									
MC	−0.2635	0.9163	1								
IL	0.1992	−0.8698	−0.7843	1							
PF	−0.2300	0.0255	0.0067	−0.0440	1						
DY	−0.0838	−0.0691	−0.0622	−0.0161	−0.1118	1					
P/E	0.0988	0.0003	−0.0226	−0.0078	0.0327	−0.1843	1				
B/P	−0.0202	0.1515	0.1446	−0.1468	0.0562	−0.1779	0.1715	1			
ROE	−0.1222	0.1144	0.1083	−0.1499	0.0236	0.0942	−0.1772	0.4506	1		
RF	0.1839	−0.1546	−0.1958	0.0874	−0.0860	0.0765	−0.0542	−0.0128	0.0902	1	
TS	0.0146	−0.0083	−0.0082	0.0238	0.0593	−0.0195	−0.0032	−0.0212	−0.0228	−0.5631	1

Note: This table shows the correlations between the sector-level factors. SD is standard deviation representing volatility. TV is (log) dollar trading volume. MC is market value in (log) millions of US dollars. IL is illiquidity. PF is excess return over the risk-free rate measured as government bond yield. DY is dividend yield. P/E is price-to-earnings ratio. B/P is book-to-price ratio. ROE is return on equity. RF is risk-free rates and TS is term spreads.

time-series predictability is stronger in economic downturns (BC = 0) than in expansion (BC = 1) as is cross-sectional predictability (Henkel, Martin, and Nardari 2011). Panel C also supports the previous finding from the statistical tests of time-series predictability (Kim, Shamsuddin, and Lim 2011). Cyclical super-sectors show a stronger variation across business cycles than other super-sectors. Their predictability may have a cyclical nature too.

Table 4 summarizes the indicators influencing time-series predictability in all sectors and markets. Clearly, the dynamic FE results tend to overstate the significance of the indicators of predictability. Therefore, we focus on the DCCE results because their estimates are unbiased under dynamic structure and cross-sectional dependence. In the DCCE results, illiquidity (IL), price downtrend, and performance (NT and PF) significantly affect time-series predictability. The indicators linked to relative valuation, operating performance, and macroeconomy do not show significance either at the sector or market level.

First, illiquidity is positively related to time-series predictability at a sector level. On the one hand, this finding verifies earlier findings that less liquid sectors deter arbitrageurs and thus have higher predictability (Chung and Hrazdil 2010a; Chordia, Roll, and Subrahmanyam 2008). Therefore, less rational investors can enjoy more success from their forecasting methods in such sectors. On the other hand, this positive relationship may partly reflect the cross-sectional link between stock returns and the illiquidity premium. It is known that investors require a premium for holding illiquid stocks (Amihud and Mendelson 1986; Amihud et al. 2015). If the illiquidity premium changes over time, it may subsequently affect time-series predictability.

Second, sectoral stock performance (PF) has a strong negative relationship with time-series predictability at the market level. In other words, stock markets with stronger (weaker) price performance have lower (higher) predictability. Downward trending markets (NT) have even higher predictability. This finding implies that less rational investors' forecasting will be more accurate in weakly performing markets. This evidence is consistent with the macroeconomic-level link between business cycles and market predictability. Stock markets are known to be more predictable during economic downturns (Henkel, Martin, and Nardari 2011) but less predictable in economic expansions (Kim, Shamsuddin, and Lim 2011). The reason could be that investors asking for a higher premium in economic downturns increase predictability (Fama and French 1989; Campbell and Cochrane 1999; Guiso, Sapienza, and Zingales 2018). However, the BC indicator does not capture this effect in the DCCE results. The implication is that the nature of this relationship is more dynamic than what a simple dummy can reflect and is overshadowed by other factors.

Third, the indicators related to company fundamentals—such as dividend yield and operating performance—have insignificant relationships with time-series predictability. Although fundamentals are important theoretical building blocks in stock-pricing models, their predictive power for stock returns is inconclusive (Paye and Timmermann 2006). For example,

Table 3. Time-Series Predictability

Sub		Sector	Market	CYC	SEN	DEF	BMAT	CODI	COST	ENEG	FINA	HLTH	INDU	RLES	TECN	TELC	UTIL
Panel A: % of rolling windows with significant predictability																	
IS	DEV	0.1277	0.1233	0.1346	0.1218	0.1248	0.1279	0.1235	0.1208	0.1281	0.1327	0.1152	0.1321	0.1539	0.1306	0.1092	0.1308
	EMG	0.1503	0.1562	0.1554	0.1543	0.1423	0.1521	0.1646	0.1548	0.1203	0.1592	0.1445	0.1506	0.1424	0.1932	0.1254	0.1617
	FRT	0.1660	0.2205	0.1738	0.1526	0.1674	0.1682	0.1471	0.1448	0.1441	0.2159	0.1835	0.1922	0.1619	0.1667	0.1642	0.1111
OOS	DEV	0.1312	0.1678	0.1275	0.1266	0.1382	0.1276	0.1089	0.1241	0.1511	0.1556	0.1380	0.1626	0.1171	0.1175	0.1209	0.1166
1	EMG	0.1398	0.1596	0.1450	0.1396	0.1347	0.1356	0.1410	0.1308	0.1055	0.1577	0.1184	0.1481	0.1448	0.1201	0.1596	0.1667
	FRT	0.1382	0.1769	0.1073	0.1687	0.1501	0.0538	0.0769	0.1615	0.1385	0.1846	0.2019	0.1462	0.1154	0.1410	0.1789	0.1429
OOS	DEV	0.1179	0.1127	0.1209	0.1122	0.1190	0.1274	0.1291	0.1182	0.1380	0.1418	0.1213	0.1109	0.0855	0.1124	0.1160	0.0949
2	EMG	0.1479	0.1660	0.1478	0.1423	0.1520	0.1529	0.1315	0.1620	0.1684	0.1707	0.1204	0.1610	0.1318	0.1593	0.1220	0.1378
	FRT	0.1758	0.2160	0.1747	0.1791	0.1744	0.1440	0.1840	0.2258	0.1440	0.2400	0.1441	0.1920	0.1200	0.2105	0.1700	0.1600
	Avg.	0.1375	0.1516	0.1417	0.1346	0.1354	0.1370	0.1368	0.1368	0.1301	0.1517	0.1297	0.1442	0.1407	0.1437	0.1218	0.1396
Panel B: Time-series predictability (PD)																	
IS	DEV	0.0119	0.0115	0.0122	0.0117	0.0117	0.0115	0.0115	0.0118	0.0117	0.0119	0.0110	0.0117	0.0137	0.0122	0.0111	0.0122
	EMG	0.0147	0.0158	0.0147	0.0150	0.0146	0.0140	0.0155	0.0151	0.0124	0.0161	0.0136	0.0160	0.0125	0.0204	0.0118	0.0160
	FRT	0.0167	0.0216	0.0159	0.0161	0.0183	0.0143	0.0165	0.0180	0.0188	0.0169	0.0173	0.0179	0.0159	0.0214	0.0170	0.0108
OOS	DEV	0.0112	0.0118	0.0110	0.0112	0.0115	0.0108	0.0116	0.0128	0.0132	0.0106	0.0105	0.0113	0.0108	0.0092	0.0125	0.0099
1	EMG	0.0139	0.0136	0.0129	0.0140	0.0147	0.0107	0.0123	0.0141	0.0128	0.0145	0.0141	0.0156	0.0142	0.0130	0.0169	0.0139
	FRT	0.0181	0.0148	0.0153	0.0212	0.0188	0.0168	0.0132	0.0185	0.0183	0.0131	0.0249	0.0158	0.0189	0.0232	0.0199	0.0210
OOS	DEV	0.0123	0.0130	0.0129	0.0112	0.0124	0.0135	0.0139	0.0112	0.0139	0.0132	0.0111	0.0125	0.0109	0.0117	0.0117	0.0112
2	EMG	0.0133	0.0161	0.0137	0.0120	0.0139	0.0152	0.0129	0.0123	0.0127	0.0157	0.0108	0.0145	0.0106	0.0155	0.0132	0.0125
	FRT	0.0165	0.0193	0.0161	0.0178	0.0159	0.0148	0.0170	0.0208	0.0128	0.0206	0.0175	0.0218	0.0108	0.0171	0.0119	0.0145

BC	Sector	Market	CYC	SEN	DEF	BMAT	CODI	COST	ENEG	FINA	HLTH	INDU	RLES	TECN	TELC	UTIL
Panel C: Time-series predictability in business cycles																
0	0.0160	0.0173	0.0156	0.0143	0.0147	0.0161	0.0160	0.0156	0.0128	0.0163	0.0139	0.0159	0.0141	0.0164	0.0125	0.0145
1	0.0138	0.0141	0.0127	0.0129	0.0127	0.0120	0.0127	0.0130	0.0127	0.0133	0.0120	0.0134	0.0127	0.0137	0.0121	0.0132

Note: Panel A shows the proportions (%) of rolling windows with significant time-series predictability identified by the Clark and West tests. Panel B presents the average values of time-series predictability (PD). IS, OOS1, and OOS2 are the in-sample, the first out-of-sample (pre-pandemic) and the second out-of-sample (pandemic) periods, respectively. Panel C shows a variation of PD in business cycles (BC = 0 for contraction and 1 for expansion). The values are grouped by sector, super-sector and market development. "Market" indicates a market-level index is tested instead of individual sectors ("Sector"). Cyclical (CYC), sensitive (SEN), and defensive (DEF) are Morningstar super-sectors. Individual sectors are basic materials (BMAT), consumer discretionary (CODI), consumer staples (COST), energy (ENEG), financials (FINA), healthcare (HLTH), industrial (INDU), real estate (RLES), technology (TECN), telecommunications (TELC), and utilities (UTIL) sectors. Market development is classified as developed (DEV), emerging (EMG), and frontier (FRT) markets.

Table 4. Time-Series Predictability and Its Indicators

		FE		DCCE	
	Indicator	Sector level	Market level	Sector level	Market level
Price and trade originated	Neg price trend	0.0154**	0.0191**	−0.0565	0.0220**
	(NT)	(0.0020)	(0.0057)	(0.0695)	(0.0073)
	Volatility	0.1131**	0.1476**	0.3110	0.0920
	(SD)	(0.0084)	(0.0206)	(0.4895)	(0.0565)
	Trading Volume	−0.0654**	−0.0683*	−0.6068	0.2105
	(TV)	(0.0136)	(0.0334)	(1.5528)	(0.1294)
	Market Cap	−0.0880**	−0.1028*	−3.1937	0.2315
	(MC)	(0.0119)	(0.0488)	(2.5916)	(0.1642)
	Illiquidity	0.0724**	0.1333	1.9790*	15.1677
	(IL)	(0.0116)	(0.0872)	(0.9750)	(10.6565)
	Stock Price Perf.	−0.0560**	−0.0926**	−0.0803	−0.1574**
	(PF)	(0.0077)	(0.0202)	(0.1421)	(0.0380)
Relative valuation	Dividend yield	0.0400**	0.0825**	0.8126	0.1415
	(DY)	(0.0095)	(0.0305)	(1.8287)	(0.0795)
	Price to earnings	−0.0154	−0.3157**	−11.9940	0.3510
	(P/E)	(0.0077)	(0.0928)	(8.3575)	(0.2510)
	Book to price	−0.0188*	−0.0566	1.4349	−0.0005
	(B/P)	(0.0076)	(0.0431)	(1.7004)	(0.2561)
Operating performance	ROE	−0.0106	−0.0012	−4.3922	0.1333
	(RE)	(0.0068)	(0.0302)	(6.6537)	(0.0788)
Macro-economic	Business cycles	−0.0424**	−0.0541**	−1.1031	−3.3305
	(BC)	(0.0038)	(0.0049)	(2.1718)	(4.2036)
	Short rates	0.0067	0.0055	−0.4613	−0.0140
	(RF)	(0.0043)	(0.0081)	(1.2966)	(0.0456)
	Term spreads	0.0023	0.0020	−1.6228	0.0098
	(TS)	(0.0048)	(0.0096)	(1.0757)	(0.0289)
	Obs	58,933	7,818	55,643	7,489
	R^2	0.0574	0.0487	0.8402	0.8832

Note: This table shows the estimation results of the model for time-series predictability. The model is estimated on the panel of all sector indices in the sample markets (sector-level) and also on the market indices (market-level). Each indicator is individually tested. FE is the fixed effects and DCCE is the dynamic common correlated effects estimators. The estimated coefficients of all lagged predictability are not included to save space. R^2 is the average value of individual results. Obs is the average number of observations (rolling windows). ** and * show the statistical significance at 1 and 5% levels, respectively. The numbers in brackets are standard errors.

dividend yield shows no strong evidence of predictability in Hjalmarsson (2010). Its link to time-series predictability could be similarly weak. Finally, other indicators related to the relative valuation of stocks, such as P/E and B/P, are not linked to time-series predictability despite their power as predictors (Kong et al. 2011; Phan, Sharma, and Narayan 2015).

Unlike the DCCE indicators, the FE estimators overstate the significance of the indicators. It could be a consequence of the limitations of FE models in ignoring cross-sectional dependence and causing a bias in dynamic models (Nickell 1981). These indicators include volatility, trading volume, and market capitalization. Similarly, the business cycle indicator (BC) is significant only in the FE models, although its sign and significance match previous studies (Guiso, Sapienza, and Zingales 2018; Fama and French 1989; Campbell and Cochrane 1999). However, the FE and the DCCE results are not essentially different in terms of the signs of estimated coefficients. Therefore, those insignificant indicators in the DCCE results deserve further investigation by subsample analysis, that is, where their cross-sectional averages are calculated within each subsample.

The first subgroup analysis compares the industry sectors of developed and emerging markets (as shown in the left panels of Table 5). The first difference between the subsample results and the whole sample's results (shown in Table 4) is the significant positive influence of volatility in both markets. In

Table 5. Predictability and Its Indicators: Subgroup Analysis

		Market development		Super-Sectors		
	Indicator	DEV	EMG	CYC	SEN	DEF
Price and trade originated	Neg Price Trend	0.0173**	−0.0006	0.0168**	0.0075	−0.1057
	(NT)	(0.0039)	(0.0093)	(0.0061)	(0.0080)	(0.1186)
	Volatility	0.1386*	0.3144**	0.4041**	0.1667*	0.3204*
	(SD)	(0.0586)	(0.0911)	(0.0929)	(0.0680)	(0.1365)
	Trading Volume	−0.2487**	0.1407	0.0451	−0.0549	−0.1183
	(TV)	(0.0924)	(0.1250)	(0.1527)	(0.1646)	(0.1340)
	Market Cap	−0.2487	−0.2843	−0.4979*	−0.3131	−0.6836
	(MC)	(0.3059)	(0.3268)	(0.2271)	(0.4116)	(1.2423)
	Illiquidity	1.0319	0.7042	7.9763*	0.9391*	0.1392
	(IL)	(0.8739)	(0.9558)	(3.6776)	(0.4486)	(0.7164)
	Stock Price Perf.	−0.1025**	−0.0636*	−0.0696	−0.0675*	0.0772
	(PF)	(0.0228)	(0.0291)	(0.0399)	(0.0298)	(0.1277)
Relative valuation	Dividend Yield	0.1661*	−0.4095	0.1326	0.1824	−0.2703
	(DY)	(0.0651)	(0.6441)	(0.1292)	(0.1157)	(0.3759)
	Price to Earnings	−0.2169	0.1298	0.6038	0.3876	−1.9246
	(P/E)	(0.2118)	(0.1834)	(0.3153)	(0.3542)	(1.6089)
	Book to Price	0.0371	0.3354	0.3412	0.2415	−0.6958
	(B/P)	(0.2796)	(0.5005)	(0.5191)	(0.3193)	(0.5970)
Operating performance	ROE	0.0225	0.6131	0.3520	0.4944	2.7856
	(RE)	(0.0588)	(0.3228)	(0.5135)	(0.3678)	(2.6536)
Macro-economic	Business Cycles	0.5151	0.0688	8.4440	−0.9673	0.4290
	(BC)	(2.5776)	(0.5253)	(8.2775)	(0.6373)	(0.8651)
	Short Rates	−0.5346	0.7130	−0.8000	−1.5451	−0.6342
	(RF)	(2.4384)	(2.4109)	(0.6935)	(1.5071)	(1.3349)
	Term Spreads	−1.7514	0.8194	0.5633*	−0.1156	−0.7320
	(TS)	(2.0911)	(0.7018)	(0.2868)	(0.4084)	(0.9444)
	Obs	31,815	21,382	19,412	19,404	13,925
	R^2	0.8799	0.8122	0.8551	0.8370	0.8496

Note: This table shows the estimation results of the model for the indicators of predictability on two sets of subgroups: market development (the developed markets versus the emerging markets) and super-sectors (the cyclical, the sensitive, and the defensive super-sectors). DEV and EMG are developed and emerging markets, respectively. Cyclical (CYC), sensitive (SEN), and defensive (DEF) are Morningstar super-sectors. The estimation uses the DCCE estimators. Not all the estimated coefficients of lagged predictability are included to save space. R^2 is the average value of individual results. "Obs" is the average number of observations (rolling windows). The numbers in brackets are standard errors. ** and * show the statistical significance at 1%, and 5% levels, respectively.

other words, less rational investors' forecasting performance is stronger in the more volatile sectors. This rather unintuitive result can happen when higher estimation uncertainty creates overall underpricing (Timmermann 1993, 1996) and the subsequent correction generates predictability over time. Therefore, even less rational investors can benefit from easy-to-detect patterns. Similar empirical evidence is shown by Kim, Shamsuddin, and Lim (2011). Another difference is the loss of significance in illiquidity. Illiquidity and the illiquidity premium are known to be larger in the emerging markets (Amihud et al. 2015) together with higher structural risk (Donadelli and Persha 2014), but they may not be linked to time-series predictability. Sector-level price performance (PF) maintains the same significant negative effect in both markets.

A notable difference between the developed and the emerging markets is that a larger trading volume reduces time-series predictability only in the developed markets. Trading volume may reflect excessive noise in the market, which reduces predictability (Phan, Sharma, and Narayan 2015). The investors in the developed markets, however, are likely to be more able, so their trading increases market efficiency while decreasing predictability. Similarly, the subgroup analysis can reveal which specific indicator is more dominant between the two types of markets. For example, the sectors in the developed market become more predictable with price downtrends (NT) or larger dividend payments (DY). Therefore, the less rational investors ought to look for information on prices and dividends in the developed markets.

Macroeconomic factors, such as business cycles, short rates, and term spreads do not show any difference between the developed and the emerging markets and they are all insignificant. This finding does not match those of earlier studies on the predictors of returns. For example, both RF and TS are strong predictors of returns (Hjalmarsson 2010), and BC affects the power of TS as a predictor in the developed markets (Henkel, Martin, and Nardari 2011; Kim, Shamsuddin, and Lim 2011). Our results show that the indicators of predictability behave differently from the predictors of returns.

The second subgroup analysis examines three super-sectors separately: cyclical, sensitive, and defensive (as shown in the right panels of Table 5). Across all three super-sectors, volatility (SD) remains as strongly relevant as in the whole sample. However, each super-sector has distinctive indicators. First, the cyclical super-sectors are associated with the largest number of indicators: NT, SD, MC, IL, and TS. The high sensitivity of cyclical super-sectors to business cycles may be behind the significance of these indicators if the indicators share this sensitivity, which can increase return predictability (Henkel, Martin, and Nardari 2011; Kim, Shamsuddin, and Lim 2011). However, the link to the business cycle indicator is not directly observable here as in the all-sample results. Next, the sensitive super-sectors have three identified indicators—SD, IL, and PF—and the defensive super-sectors have only one—SD. This finding shows that volatility is a universal indicator of predictability across super-sectors whereas the other indicators are likely to be related to the business cycle to some degree.

In summary, stronger time-series predictability can be found from eight indicators in specific sectors as follows: (1) price downtrends, specifically in the developed markets and cyclical super-sectors; (2) higher volatility in general; (3) higher illiquidity, particularly in cyclical and sensitive super-sectors; (4) lower price performance in the sensitive super-sectors; (5) lower trading volume in the developed markets; (6) smaller market capitalization in the cyclical super-sectors; (7) higher dividend yields in the developed markets; and (8) larger term spreads in the cyclical super-sectors.

Table 6. Predictability Gains

		Subperiod		
		IS	OOS1	OOS2
1) Neg price trend in CYC/DEV	Selected	0.1613	0.1661	0.1792
	Rest	0.1521	0.1468	0.1416
	Gain	0.0092	0.0193	0.0376
2) Volatility in All	Selected	0.2346	0.3035	0.2812
	Rest	0.1528	0.1509	0.1522
	Gain	0.0818	0.1526	0.1290
3) Trading volume in DEV	Selected	0.1716	0.3113	0.1816
	Rest	0.1553	0.1537	0.1550
	Gain	0.0162	0.1575	0.0266
4) Market cap in CYC	Selected	0.1656	0.1929	0.1682
	Rest	0.1553	0.1537	0.1549
	Gain	0.0104	0.0392	0.0133
5) Illiquidity in CYC/SEN	Selected	0.1933	0.1962	0.1665
	Rest	0.1544	0.1532	0.1549
	Gain	0.0389	0.0430	0.0115
6) Stock Price Perf. in SEN	Selected	0.1781	0.2072	0.1844
	Rest	0.1546	0.1529	0.1540
	Gain	0.0236	0.0543	0.0304
7) Dividend yield in DEV	Selected	0.1606	0.1922	0.2470
	Rest	0.1555	0.1541	0.1549
	Gain	0.0051	0.0381	0.0921
8) Term spreads in CYC	Selected	0.1721	0.1599	0.2141
	Rest	0.1549	0.1545	0.1543
	Gain	0.0172	0.0055	0.0598
	Avg. Gain	0.0253	0.0637	0.0500

Note: This table presents the net gains in normalized time-series predictability for the chosen sectors ("Selected") against the unselected sectors ("Rest") based on each identified indicator. The selected sectors are the top 10 sectors in terms of the largest or the smallest values of the corresponding indicators in specific super-sectors or markets. CYC and SEN are cyclical and sensitive super-sectors, respectively. DEV is the developed markets. IS, OOS1, and OOS2 are the in-sample, the first out-of-sample (pre-pandemic), and the second out-of-sample (pandemic) periods, respectively,

In terms of subgroups, first, in all sectors, the more volatile sectors are more predictable. Second, in the developed markets, stronger predictability is expected with price downtrends, lower trading volume, and higher dividend yields. Third, the emerging markets do not have such relationships. Fourth, in the sensitive super-sectors, predictability increases when liquidity and price performance decrease. Finally, in the cyclical super-sectors, higher predictability is linked to down-trending price, smaller market size, and larger term spread. By investing in these sectors, the less rational trader can obtain higher predictability while enjoying better diversification than investing in individual stocks.

Table 7. Return Gains

		Net gains: sector investing			Gains over the market		
		IS	OOS1	OOS2	IS	OOS1	OOS2
Volatility	BST	−0.3783	−1.3113	−2.3201	−0.1600	−1.2419	−1.6943
in All	MOM	0.3523	0.4939	−3.7823	0.5048	0.8175	−3.7400
	B&H	−0.3441	0.4242	−1.9624	−0.2367	0.3327	−1.8646
Trading Volume	BST	−0.4149	−4.8177	−2.6678	−0.2016	−4.7587	−2.0759
In DEV	MOM	0.1983	−3.3434	−0.9774	0.3580	−2.9978	−1.0087
	B&H	0.5227	−2.2586	−1.6213	0.6122	−2.3333	−1.5556
Market Cap	BST	0.5187	−0.3250	−0.8676	0.7099	−0.2761	−0.2721
In CYC	MOM	0.6959	0.3915	0.5082 Y	0.8370	0.7171	0.4610 Y
	B&H	0.6667	0.1545	0.6809 Y	0.7435	0.0686	0.7235 Y
Illiquidity	BST	0.0686	−0.2604	−0.3247	0.2737	−0.2129	0.2595
In CYC/SEN	MOM	0.1717	1.0290	0.5552 Y	0.3292	1.3413	0.5070 Y
	B&H	0.7889	0.2809	1.3151 Y	0.8631	0.1923	1.3445 Y
Dividend Yield	BST	0.5926	1.4691	−4.4736	0.7913	1.5045	−3.8805
In DEV	MOM	0.5097	0.7556	−2.7365	0.6650	1.0859	−2.7635
	B&H	0.2472	0.0100	3.1645 Y	0.3409	−0.0728	3.2102
Term Spreads	BST	0.6532	−0.4765	−1.6009	0.8389	−0.4234	−0.9839
In CYC	MOM	0.3984	−0.7888	−2.5031	0.5479	−0.4367	−2.4779
	B&H	0.1987	0.4613	0.1574 Y	0.2895	0.3680	0.2103 Y

Note: This table presents the average gains in percentage returns over 25 trading days when investing in the selected sectors in specific super-sectors or markets based on each identified indicator. The gains are calculated from three trading strategies: the best previous forecasting method (BST), the naive/momentum (MOM), and the simple sector buy-and-hold (B&H) against the non-selected sectors (left panel) and the market returns (right panel). Y indicates that the corresponding strategies show consistent gains in three subperiods. IS, OOS1, and OOS2 are the in-sample, the first out-of-sample, and the second out-of-sample periods, respectively. CYC and SEN are cyclical and sensitive super-sectors, respectively. DEV is the developed markets.

Whether these findings deliver economic significance to investors is another question. First of all, we need to examine whether the sectors selected by the eight indicators just listed do indeed provide higher predictability and whether such predictability is persistent in the out-of-sample periods. Table 6 summarizes the net predictability gains in the selected eight groups of sectors over the rest of the sectors. Clearly, the selected sectors can provide persistently higher predictability than the other sectors in all eight groups, although the absolute size of the predictability gain is not large. The gain is not only positive in the in-sample period (IS) but also positive in both out-of-sample periods (OOS1 and OOS2). The impact of the COVID-19 pandemic on predictability is not obvious.

Therefore, trading strategies can be devised to generate economic significance—for example, higher returns—from stronger predictability. Table 7 presents the net return gains in sector investing when building trading strategies based on the six indicators in our study. We exclude two indicators, NT and PF, because they are directly linked to sector price performance and thus are not ideal when calculating gains in sector-level returns. Specifically, we test the simple buy-and-hold strategy in sector investing (B&H) and two variants with forecasting elements—buy or sell following momentum (MOM) and the previous best forecasting method (BST).

The results are summarized in terms of the net gains over the nonselected sectors (left panel) and the net gains over the market buy-and-hold strategy (right panel). Table 7 shows that the return gains are limited to certain indicators and trading strategies. For example, the B&H strategy generates consistently higher return gains against the market and the rest of the sectors when tested in the sectors with the larger market cap, higher illiquidity, and larger term spreads. The magnitude of the return gains from profitable trading strategies in these sectors reaches, on average, about 0.6% over 25 trading days (or 6% over 250 trading days). The MOM strategy is also profitable in large or highly illiquid sectors. These gains were not affected by the COVID-19 pandemic

(OOS2). We assume that the trading costs when adopting the market B&H strategy and the three tested trading strategies are similar for the same amount of investment since the tested strategies are also buy-and-hold approaches at a sector level. BST, however, which requires certain time-series forecasting skills, does not beat the market. This finding implies that any other sophisticated strategies, which need more complex forecasting or frequent trading than B&H and MOM, may find it difficult to generate sufficient gains to be usable because they are likely to be even more costly. However, it is also fair to note that we did not test a large number of the available trading strategies.

Conclusion

We have described our investigation of the relationship between time-series predictability and its sector-level indicators. We focused on investors who are searching for higher predictability for sector investing but are not as well informed as other investors. We examined 11 industry sectors across 47 international stock markets based on the dynamic fixed-effects and the dynamic common correlated effects models. The sample period covers two out-of-sample periods, including the COVID-19 pandemic period.

The main takeaway from this study is identification of the indicators of sector-level time-series predictability. Specifically, our key findings are as follows: Time-series predictability differs across sectors and is linked to the indicators of predictability at a sector level. Investors can expect stronger time-series predictability by carefully choosing sectors based on specific indicators. For example, in the developed markets, they can select sectors with down-trending prices, lower trading volumes, and higher dividend yields. To invest in the cyclical or sensitive super-sectors—that is, for business cycle investing—highly illiquid sectors or those in in which prices are underperforming are good destinations for investing based on higher predictability. For the cyclical super-sectors, investors can also choose small sectors in the markets where term spreads are large. They can also generally go for the more volatile sectors for higher predictability. The roles of company fundamentals and relative valuation are limited. Using the chosen indicators, investors could have consistently enjoyed strong predictability gains even in out-of-sample periods, including the COVID-19 pandemic period. They could have also obtained return gains by following certain indicators and using simple trading strategies.

This study offers comprehensive evidence of the indicators of time-series predictability and shows how they can be used to generate consistent predictability and economic gains for sector investing. Our study provides important implications along several dimensions that are of relevance to both academics and investors. First of all, we provide forward-looking indicators for investors who seek the more predictable sectors where they can attempt to generate more profits. We essentially show that time-series predictability displays sector-level heterogeneity identifiable by the indicators. These indicators can help even investors who are not able or willing to use all available information. Additionally, we provide the methods of measuring time-series predictability using investors' forecasting as defined in our study. We find that the impact of the COVID-19 pandemic on time-series predictability and its indicators has been limited.

Some limitations of this study could be addressed by future research. A natural extension to sector investing could be the examination of individual company stocks and other investment portfolios, such as growth, value, large-cap, and small-cap portfolios. Other factors, such as investor sentiment and attitude, and industry specifics, such as competition, concentration, regulatory changes, and external events, could also be examined. Moreover, future extensions could include using an index like the one developed by Narayan, Iyke, and Sharma (2021) for more comprehensive tests of the impact of the COVID-19 pandemic and tests of profitability for several active trading strategies.

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