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Macroeconomics matter: Leading economic indicators and the cross-section of global stock returns

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ABSTRACT

Leading economic indicators assist in forecasting future business conditions. Can they also predict aggregate stock returns? To answer this question, we examine six decades of data from 39 countries. Short-term changes in the composite leading indicator (CLI) positively correlate with future stock returns in the cross-section. The quintile of markets with the highest CLI increase outperforms the quintile with the lowest CLI change by 1.43% per month. The predictive power of the CLI survives multiple robustness checks and cannot be absorbed by established risk factors. Our findings imply an exploitable investment strategy that can be pursued with exchange-traded funds.

1. Introduction

Leading economic indicators give a glimpse into the future state of the economy. Composed of forward-looking measures, they tend to precede the business cycle by several months. But can they also help to forecast future stock returns? Studies in the asset pricing literature demonstrate that macroeconomic variables can influence the equity premium even in informationally efficient markets.[1] Moreover, if a market is not fully efficient, underreaction to macroeconomic news may also skew the equity premium.[2] Previous

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[1] For comprehensive studies of multiple variables, see, for example, Flannery and Protopapadakis (2002), Rapach et al. (2005), Campbell and Thompson (2008), Goyal and Welch (2008), Rapach et al. (2010), Johnson (2018), Rapach and Zhou (2020), Goyal et al. (2021), and Hollstein et al. (2021).

[2] Investor underreaction is the tendency of stock prices to gradually respond to the arrival of new information. The behavioral finance literature provides abundant evidence of underreaction to firm-specific announcements. For example, in the context of post-earnings announcement drift (Bernard and Thomas, 1989, 1990), stock responses to different corporate events (Ikenberry et al., 1995; Loughran and Ritter, 1995; Michaely et al., 1995) or return momentum and autocorrelation (Jegadeesh and Titman, 1993). The underreaction to macroeconomic news was discussed, for example, in Basu et al. (2010), Baur et al. (2012), Hann et al. (2012), Hong and Yogo (2012), Wang (2015), Hugon et al. (2016), Brooks et al. (2018), Law et al. (2018), Niu (2019), Condie et al. (2021), Liang et al. (2021), and Niu and Terry (2021).

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studies attribute such phenomenon to investor conservatism, anchoring on economic data, or slow-moving capital.[3]

Regardless of the underlying mechanism, if investors underestimate the innovations associated with leading economic indicators, the market may fail to properly perceive the future business environment. Consequently, variations in leading economic indicators may contain information about future stock returns. In this study, we examine the effectiveness of such indicators regarding country-level equity premium forecasts. Specifically, we propose a new return predicting signal: the monthly change in the OCED's composite leading indicator (ΔCLI) and investigate its predictive power with respect to the cross-section of global stock returns using six decades of data from 39 countries.

Our findings suggest that ΔCLI is a powerful predictor of country-level stock returns, as an equal-weighted quintile of markets with the highest ΔCLI outperforms their low ΔCLI counteracts by 1.43% per month. Importantly, the abnormal returns on the spread portfolios are robust to both different weighting schemes and portfolio designs, and they survive a comprehensive set of well-established global and local asset pricing models.

Our bivariate sorts and cross-sectional regressions further confirm that the impact of ΔCLI is not subsumed by a battery of additional variables, such as market size, value, momentum, short-term reversal, long-term reversal, idiosyncratic volatility, beta, skewness, seasonality, or credit risk, making ΔCLI both a novel and independent asset pricing factor, rather than some well-known anomaly in disguise.

The predictive power of ΔCLI is distinctly robust. A trading strategy based on sorting ΔCLI produces substantial abnormal returns across different estimation periods, as well as alterative choices of months between the ΔCLI calculation and portfolio formation. We also show that such an anomaly does not depend on currency conversion and is not driven by FX markets, as it can be detected in both U.S. dollar-denominated and local currency returns.

Furthermore, we find that the return pattern associated with ΔCLI is not sensitive to the choice of markets and study period. Such effect can be detected in markets that differ in size, liquidity, development, cultural traits, shareholder protection standards, and accounting quality across various periods. The magnitude of the ΔCLI-driven mispricing is also remarkably stable. Unlike many other anomalies, it has remained significant over the last two decades, as well as in the 21st century. Moreover, the cross-sectional pattern also holds under different market and economic conditions, including volatility, valuation, liquidity, geopolitical risk, economic uncertainty, and investor sentiment.

Last but not least, we show that the effectiveness of ΔCLI cannot be explained by a range of alternative economic mechanisms. For example, it is not driven by the level, structure, or dynamics of interest rates. Similarly, the ΔCLI effect is not a manifestation of either macroeconomic or bond market momentum. Finally, it is not explained by changes in government indebtedness or a range of political and governance factors. Overall, these empirical results all indicate that the underreaction hypothesis is likely to be the underlying working mechanism of ΔCLI.

Our findings have direct practical implications. The ΔCLI effect may be translated into a country selection strategy for investors with an international mandate. As demonstrated in additional tests, the returns on the long-short portfolio based on ΔCLI do not exhibit a sizable correlation with other well-known country-level factors. Consequently, including ΔCLI strategies in a portfolio can substantially improve the overall risk-return profile by boosting the ex-post Sharpe ratios.

While we test the ΔCLI effect in country-specific equity indices, in practice it could be successfully exploited via single-country exchange-traded funds (ETFs). In an additional analysis, we utilize a sample of 30 liquid ETFs to document that such an effect holds therein as well. A long-short strategy that is notably implemented within this asset class produces excess returns between 0.50% and 0.97% per month, depending on various portfolio designs and specifications. Furthermore, the ΔCLI premium may also be effectively exploited using long-only portfolios that can circumvent potential trading difficulties caused by the short-selling constrict.

One potential caveat of the ΔCLI strategy (from an investor's angle) is its relatively high turnover as the necessity to replace roughly 30% of the portfolio each month may lead to excessive trading costs. This problem, however, can be moderated by extending the holding period since the ΔCLI effect is somewhat resilient through time. Particularly, we show that the abnormal returns remain significant even if a portfolio is reconstructed only once in nine months.

Our study is related to two main streams of the finance literature. First, we contribute to the studies of the cross-sectional predictability of country equity risk premia. Studies document variables such as value (Kim, 2012; Angelidis and Tessaromatis, 2017; Ellahie et al., 2020), momentum (Balvers and Wu, 2006; Bhojraj and Swaminathan, 2006), size (Keppler and Traub, 1993; Fisher et al., 2017), credit risk (Avramov et al., 2012), and idiosyncratic volatility (Bali and Cakici, 2010; Umutlu, 2015, 2019) are priced in the global stock returns. To our best knowledge, ours is the first study to demonstrate that the dynamics of leading economic indicators help to explain the cross-section of country index returns.

Second, we add to the literature on predicting stock returns using information contained in macroeconomic variables. Related studies have, thus far, considered a broad range of macroeconomic indicators, including inflation, unemployment, interest rates, and spreads, among many others (for recent comprehensive studies, see Flannery and Protopapadakis, 2002; Rapach et al., 2005; Goyal and Welch, 2008; Campbell and Thompson, 2008; Rapach et al., 2010; Johnson, 2018; Rapach and Zhou, 2020, 2022; Hollstein et al., 2021; and Goyal et al., 2021). Our paper differs from these studies in two aspects. First, rather than focusing on the time series predictability of the equity premium, we concentrate on the cross-sectional predictability in broad international markets. Second, we extend the literature by providing firm support to the effectiveness of leading indicators and exploring their dynamics (Chauvet and

[3] See: for investor conservatism: Barberis et al. (1998). For inattention: Gilbert et al. (2012) and Barberis (2018). For anchoring on economic data: Campbell and Sharpe (2009), Hess and Orbe (2013), and Birz et al. (2021). For slow-moving capital: Duffie (2010), Greenwood et al. (2018), Pitkäjärvi et al. (2020), and Zaremba et al. (2021).

Potter, 2000; Chen, 2009; Gilbert et al., 2012; Zhu and Zhu, 2014). For example, Zhu and Zhu (2014) scrutinize the predictive power of the prime business cycle leading indicator for the European stock markets, focusing on the time series context.

The remainder of the article proceeds as follows. In Section 2, we present the data and variables. In Section 3, we summarize the main empirical findings. In Section 4, we provide further insights and robustness checks. In Section 5, we discuss practical investor considerations. Finally, we conclude in Section 6.

2. Data and variables

2.1. Sample preparation and data sources

The sample encompasses 39 global stock markets in both developed and developing countries. The full list is provided in Table 1. The study period is from January 1967 to March 2021; nonetheless, we also use earlier data to calculate certain control variables. The timeline and composition of the final sample are dictated by the availability of both economic and stock market data.

Following Baltussen et al. (2021), we maximize the size and quality of our sample by merging data from several sources. The most recent country-level stock market performance is measured with the Datastream Global Equity Indices obtained from Datastream.[4] Their calculation is based on value-weighted portfolios that represent the majority of the liquid and investable equity universe in each of the markets considered (Thomson Reuters, 2008). As the Datastream Global Equity Indices usually cover more recent periods, we further expand the sample by appending the Global Financial Data (GFD) Equity Indices for the same markets. The GFD indices offer a unique overview of long-run historical data on stock returns and, thus, have been employed in many recent studies of risk premia in global markets (e.g., Zhang and Jacobsen, 2013; Albuquerque et al., 2015; Muir, 2017; Danielsson et al., 2018; Hjalmarsson, 2010; Bekaert and Mehl, 2019; Miranda-Agrippino and Rey, 2020; Baltussen et al., 2021). The total number of markets we cover in the paper grows gradually, from 11 in 1967 to 37 in 2021. The aggregate capitalization also grows substantially, from less than USD 1 trillion in 1967 to more than USD 80 trillion in 2021. Fig. 1 provides a graphic illustration of our equity universe.

To cope with foreign exchange risk and currency conversion issues, we follow Fama and French (2012, 2017) and express all the returns and market data in U.S. dollars. Consistent with this approach, we proxy the risk-free rate used to obtain excess returns with the one-month U.S. T-bill rate from French (2021). Table A1 in the Internet Appendix provides the summary statistics of the equity indices covered in our study.

2.2. The composite leading indicator

Our principal variable of interest is the change in the OECD Composite Leading Indicator (CLI), sourced from OECD (2021). The CLI was originally designed to "provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level".[5] Swings in the CLI are typically followed by the corresponding phases of the business cycle. According to the OECD's instructions, the CLI signals should precede the actual changes in economic activity by approximately six to nine months. For illustration, in Fig. 2 we plot the dynamics of the global CLI against the recession periods.

The CLI values are computed by aggregating various time series that exhibit evident leading relationships with dynamics of gross domestic product, especially at its turning points. The components series differ for each country and are chosen based on a range of criteria, including economic importance, data quality, cyclical behavior, availability, and timeliness. For example, the CLI series for the U.S. is based on seven components, such as the work started for dwellings, net new orders for durable goods, consumer and industrial confidence indicators, etc.

We examine whether investors fully incorporate the information concealed in the changes in expected economic conditions. Specifically, our main return predictive variable is the monthly change in the CLI value, defined as follows:

$$\Delta CLI_{i,t} = CLI_{i,t-2} - CLI_{i,t-3}, \tag{1}$$

where $\Delta CLI_{i,t}$ is the change in CLI used to predict the equity market return of country i in month t, and both $CLI_{i,t-2}$ and $CLI_{i,t-3}$ are CLI values of the same country in months t-2 and t-3, respectively. Note that the $\Delta CLI_{i,t}$ calculation implements a one-month skipping period between the calculation and prediction periods. This arrangement is aimed to avoid the look-ahead bias. The OECD leading indicators are typically published between the 8th and 17th of the month subsequent to the one they concern. For example, the indicators for July 2021 were released on August 10, 2021, and the indicators for August 2021 were published on September 14, 2021.[6] Within our baseline framework, we employ the difference between indicators of these two dates to predict stock returns for October 2021. However, as a robustness check, we also consider different prediction periods ranging from three months to 12 months, as well as other choices of skipping periods, including two or three months.

[4] See: https://www.refinitiv.com/en.

[5] See, https://data.oecd.org/leadind/composite-leading-indicator-cli.htm.

[6] The detailed release dates are available from OECD at: https://www.oecd.org/sdd/leading-indicators/scheduleforcompositeleadingindicatorupdates.htm.

Table 1
Countries covered in the study. The table lists the countries covered in the study.

No.	Country	No.	Country	No.	Country
1	Australia	14	Greece	27	Norway
2	Austria	15	Hungary	28	Poland
3	Belgium	16	India	29	Portugal
4	Brazil	17	Indonesia	30	Russia
5	Canada	18	Ireland	31	Slovakia
6	Chile	19	Israel	32	Slovenia
7	China	20	Italy	33	South Africa
8	Czechia	21	Japan	34	Spain
9	Denmark	22	Korea	35	Sweden
10	Estonia	23	Luxembourg	36	Switzerland
11	Finland	24	Mexico	37	Turkey
12	France	25	The Netherlands	38	United Kingdom
13	Germany	26	New Zealand	39	United States

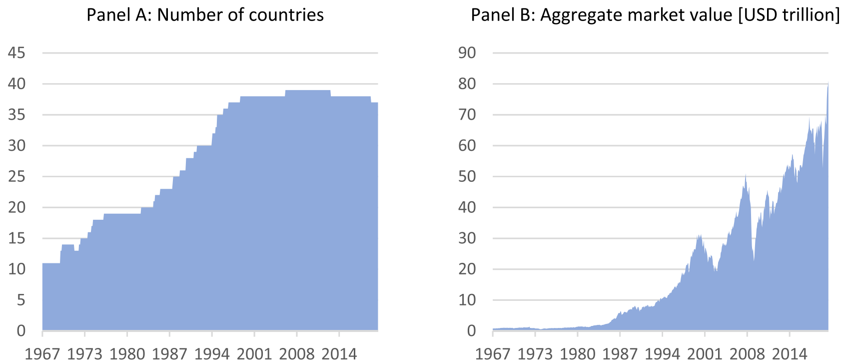

Fig. 1. Research sample. This figure shows the research sample through time. Panel A displays the total number of markets countries covered in the study, and Panel B shows their aggregate market capitalization in USD trillion. The calculations are based on 39 international stock markets. The study period is February 1967 to March 2021. Panel A: Number of countries Panel B: Aggregate market value [USD trillion].

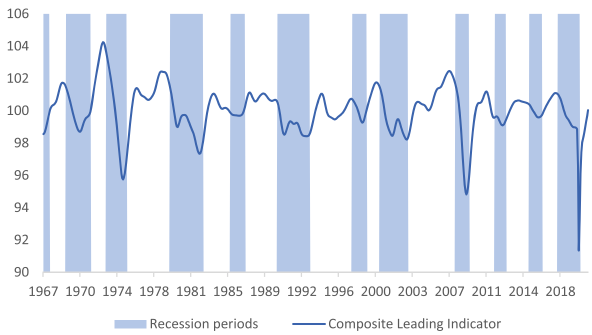

Fig. 2. Composite Leading Indicator and recessions. The figure presents the aggregate OECD Composite Leading Indicator plotted against the recession indicators from the peak through the trough. The reported period is February 1967 to March 2021. Both series are calculated for the total OECD area. The data sources are OECD (2021) and the Federal Reserve Bank of St. Louis (2021).

2.3. Control variables

In addition to *ΔCLI*, we account for a typical set of control variables that have been employed in previous studies of the cross-section of country-level returns. The market size (*SIZE*) is measured by its log-market value (Keppler and Traub, 1993; Fisher et al., 2017). The valuation effect (*VAL*), in turn, is proxied by the 12-month dividend yield (Kim, 2012; Angelidis and Tessaromatis, 2017; Ellahie et al., 2020). Although previous studies also adopt other valuation ratios, such as book-to-market ratio or earnings yield, we opt for the dividend yield due to its superior data availability. Nevertheless, this choice has no qualitative impact on our findings.[7] Furthermore, we account for three different measures of past return: short-term reversal (*SREV*), momentum (*MOM*), and long-term reversal (*LREV*), which are computed as the total log-returns in months *t*-1, *t*-12 to *t*-2, and *t*-60 to *t*-13, respectively (Balvers et al., 2000; Balvers and Wu, 2006; Bhojraj and Swaminathan, 2006; Malin and Bornholt, 2013). It is noteworthy that even though several studies (Blitz and Van Vliet, 2008; Zaremba et al., 2019) argue that country-level equity indices are mostly characterized by short-term (one-month) momentum rather than reversal, we still control it separately since this variable also contains independent information about future returns.

Meanwhile, we include stock market beta (*BETA*) and idiosyncratic risk (*IVOL*) to measure country-level systematic and specific risk components (Bali and Cakici, 2010; Frazzini and Pedersen, 2014; Umutlu, 2015, 2019; Zaremba, 2020). These two variables are computed using the global capital asset pricing model (CAPM) regression model and 36 months of trailing data. Furthermore, motivated by Baltas and Salinas (2019) and Harvey (2000), we also control for the effect of skewness (*SKEW*) of the return distribution computed using the product-moment measure for the same 36-month rolling period.

In addition, we also account for the well-known return seasonality (*SEAS*) effect in our main specification. This effect is first documented in Heston and Sadka (2008), who show that stocks with high average returns in a given calendar month in the past tend to overperform in the same calendar month in the future. Keloharju et al. (2016) extend this evidence to equity indices. Recently, Baltussen et al. (2021) regard this phenomenon as one of the most important factor premia in finance. Here we use the average same-calendar month log-return over the past 20 years to capture the *SEAS* effect in the country-level equity premium forecast.

Lastly, following Avramov et al. (2012), we control for the credit risk asset pricing effects (*CRED*). We use a simplified approach because the coverage of our long-run sample by any sovereign ratings is relatively limited. Specifically, we calculate the average cross-sectional z-scores associated with the last available debt-to-GDP ratio and the primary balance.[8]

Panel A of Table 2 reports the summary statistics, while Panel B presents the corresponding pairwise correlation coefficients. Notably, ΔCLI does not exhibit a substantial correlation with any of the other return predictors.

3. Baseline empirical findings

3.1. Univariate portfolio sorts

We begin our investigations with univariate portfolio sorts. In each month, we sort all the markets in our sample into quintiles based on ΔCLI and form equal- and value-weighted portfolios.[9] We then build spread portfolios that take a long (short) position in the quintile of countries with the highest (lowest) ΔCLI. The performance of such zero-investment strategies may serve as a simple acid test for the monotonic patterns in the cross-section of returns.

As there is limited consensus on the optimal asset pricing model for country-level equity returns, we develop ad hoc counterparts of several well-known stock-level models to capture the cross-section of stock returns. These models include: 1) the capital asset pricing model (CAPM); 2 the Fama and French (1992, 1993) three-factor model (FF3); 3) Carhart's (1997) four-factor model in its standard form (CAR4); 4) Carhart's (1997) four-factor model with an additional factor to account for the short-term (one-month) momentum (CAR5); and 5) the three-factor model (AMP) in the style of Asness et al. (2013). Lastly, we build a comprehensive model (COMP) that requires no assumptions concerning the relative importance of different country-level return predictors from the asset pricing literature: It simply incorporates all 11 control variables listed in Subsection 2.3.

Specifically, the COMP model nests all the other sparser models and can be expressed as follows:

$$\begin{aligned} R_t = {} & \alpha_{COMP} + \beta_{MKT} MKT_t^F + \beta_{SIZE} SIZE_t^F + \beta_{VAL} VAL_t^F \\ & + \beta_{MOM} MOM_t^F + \beta_{SMOM} SREV_t^F + \beta_{LREV} LREV_t^F + \beta_{IVOL} IVOL_t^F \\ & + \beta_{BETA} BETA_t^F + \beta_{SKEW} SKEW_t^F + \beta_{SEAS} SEAS_t^F + \beta_{CRED} CRED_t^F + \varepsilon_t, \end{aligned} \tag{2}$$

where R_t denotes the excess return on the examined portfolio; MKT_t^F denotes the market risk factor; $SIZE_t^F$, VAL_t^F, MOM_t^F, $SREV_t^F$, $LREV_t^F$, $IVOL_t^F$, $BETA_t^F$, $SKEW_t^F$, $SEAS_t^F$, and $CRED_t^F$ denote payoffs on long-short portfolios derived from cross-sectional sorts on *SIZE, VAL, MOM, SREV, LREV, IVOL, BETA, SKEW, SEAS*, and *CRED*, respectively (we utilize subscripts "F" to distinguish between the factor portfolios and their underlying return predictors). The β coefficients with relevant subscripts are the estimated measures of exposure, α_{COMP} denotes the average abnormal return ("alpha"), and ε_t denotes the error term. The procedures for factor construction are in Table A2 in the Internet Appendix.[10] In addition, in Table A3 therein we summarize the basic statistical properties of the factor returns.

[7] When we consider alternative valuation ratios, none of them can explain the examined phenomenon.

[8] Importantly, to assure the robustness of our approach, we cross-check it with two measures available for a limited subperiod (and subset) of our sample: the quantified average credit risk rating (as in Avramov et al., [2012]), and the Financial Risk Score by the PRS Group. The results remain qualitatively unaffected.

[9] These portfolios are rebalanced on a monthly basis.

[10] The most common approach involves creating value-weighted factor portfolios using 30th and 70th percentiles as breakpoints (Hollstein et al., 2021). By contrast, we employ the 20th and 80th percentiles, and weight the factor components either equally or according to market capitalization, depending on the scheme of the tested portfolios. This approach ensures that any abnormal returns in the mean-variance spanning tests come from the trading signal performance, and not from the differences in portfolio construction. In unreported analyses, we experiment with the alternative setup and the results are qualitatively similar.

Table 2

Statistical properties of major variables. The table reports the statistical properties of the major variables used in this study: excess stock return (*R*), the monthly change in the leading indicator (*ΔCLI*), market size (*SIZE*), dividend yield (*VAL*), short-term reversal (*SREV*), momentum (*MOM*), long-term reversal (*LREV*), idiosyncratic risk (*IVOL*), global market beta (*BETA*), skewness (*SKEW*), seasonality (*SEAS*), and credit risk (*CRED*). Panel A reports the basic descriptive statistics: mean, standard deviation, skewness, minimum, quartiles, maximum, and the number of country-month observations. Panel B presents average cross-sectional pair-wise correlation coefficients. The values above the diagonal are Pearson's product-momentum coefficients, and the values below the diagonal are Spearman's rank-based coefficients. The sample covers 39 markets. The study period is from February 1967 to March 2021. The returns are cumulated additively and are expressed in percentage terms.

	R	ΔCLI	SIZE	VAL	SREV	MOM	LREV	IVOL	BETA	SKEW	SEAS	CRED
Panel A: Descriptive statistics												
Mean	0.008	0.000	10.030	1.214	0.011	0.008	0.008	0.060	0.842	−0.041	0.011	0.011
Std. Dev.	0.085	0.007	2.690	2.888	0.085	0.031	0.017	0.045	0.828	0.691	0.018	2.039
Skewness	1.344	−2.692	−0.322	3.347	1.354	−0.715	0.630	4.044	15.897	0.015	0.588	43.127
Minimum	−0.955	−0.239	0.336	0.000	−0.955	−0.365	−0.274	0.000	−29.478	−4.501	−0.063	−1.699
1st quartile	−0.031	−0.002	8.288	0.022	−0.028	−0.007	0.000	0.035	0.478	−0.425	0.000	−0.664
Median	0.007	0.000	10.092	0.034	0.010	0.008	0.007	0.048	0.847	−0.049	0.010	−0.013
3rd quartile	0.046	0.002	11.909	0.065	0.049	0.023	0.016	0.072	1.152	0.325	0.022	0.641
Maximum	1.725	0.227	17.502	26.500	1.726	0.327	0.327	0.723	54.247	3.946	0.138	106.685
#Obs.	31,418	31,419	31,420	31,421	31,422	31,423	31,424	31,425	31,422	31,427	31,428	31,429
Panel B: Pairwise correlation coefficients												
R		0.095	−0.030	0.028	0.080	0.071	−0.038	0.038	−0.023	0.010	0.008	−0.011
ΔCLI	0.080		−0.009	0.000	0.118	0.105	−0.046	0.016	−0.015	0.034	0.003	0.008
SIZE	−0.011	−0.025		−0.424	−0.004	0.028	0.066	−0.362	0.319	−0.199	0.012	−0.049
VAL	0.031	−0.033	−0.348		0.009	0.006	−0.001	0.128	−0.248	0.064	0.012	0.032
SREV	0.065	0.097	0.012	−0.030		0.092	−0.035	0.050	−0.022	0.045	0.021	−0.007
MOM	0.066	0.097	0.035	−0.094	0.080		−0.010	0.067	−0.079	0.089	0.036	−0.052
LREV	−0.028	−0.039	0.075	−0.099	−0.025	−0.010		0.115	−0.089	0.006	0.084	−0.168
IVOL	−0.002	0.016	−0.369	0.020	0.002	0.028	0.061		0.005	0.275	0.084	−0.042
BETA	−0.003	−0.025	0.388	−0.221	−0.004	−0.028	−0.020	−0.005		−0.105	0.021	0.038
SKEW	−0.003	0.032	−0.214	−0.009	0.003	0.058	−0.040	0.244	−0.107		0.037	0.039
SEAS	0.020	−0.002	0.005	0.001	0.020	0.039	0.086	0.059	0.009	0.028		−0.083
CRED	−0.010	0.017	−0.051	0.011	−0.006	−0.052	−0.163	−0.040	0.019	0.043	−0.076	

The sparser models include smaller sets of factors from equation (2). Specifically, for CAPM: $\{MKT_t^F\}$; for FF3: $\{MKT_t^F, SIZE_t^F, VAL_t^F\}$; for AMP: $\{MKT_t^F, VAL_t^F, MOM_t^F\}$; for CAR4: $\{MKT_t^F, SIZE_t^F, VAL_t^F, MOM_t^F\}$, and finally, for CAR5: $\{MKT_t^F, SIZE_t^F, VAL_t^F, MOM_t^F, SREV_t^F\}$.

Table 3 reports the returns on the portfolios from one-way sorts of *ΔCLI*. A quick overview reveals a powerful and robust cross-sectional pattern. The average portfolio returns increase along with *ΔCLI*. The average differential return between the equal-weighted (value-weighted) top and bottom *ΔCLI* quintiles equals 1.43% (1.37%). Furthermore, the returns on the spread strategies survive the application of different factor models. Even the most comprehensive 11-factor model cannot explain the abnormal returns, and the corresponding alphas amount to 1.23% (1.20%) for the equal-weighted (value-weighted) framework.

As argued in Harvey et al. (2016), many predictive signals in the asset pricing literature may, in fact, originate from mere statistical artifacts, making the traditional 5% significance threshold too loose to unveil the underlying economic relation. Given the risk of the so-called type I error, that is, incorrectly rejecting a correct hypothesis, Harvey et al. (2016) advocate the use of a stricter hurdle, one with the absolute *t*-statistic higher than 3.0. Notably, all the relevant *t*-statistics in Table 2 unequivocally pass this threshold. The lowest *t*-values on the spread portfolios exceed 5.0, which largely alleviates the data mining concerns.

In addition to the portfolio performance from one-way sorts, we are also interested in both their composition and changes over time. We want to know whether the abnormal returns are generated by a constant set of countries or whether the portfolio structure changes dynamically through time. In order to explore these questions, we calculate the proportion of time each country is included in different quintile portfolios.

We summarize the results in Panel A of Table 4. We find that the composition of the portfolios is not constant through time. The countries in our sample dynamically migrate across different *ΔCLI* quintiles. For most countries, we do not detect any substantial bias towards the top or bottom portfolios only.

Panel B of Table 4 presents the turnover ratios for the quintile portfolios. We calculate the turnover scores following the approach of Bollerslev et al. (2018) and Koijen et al. (2018), where we replace the average share of the portfolio each month. The respective values for the extreme (high or low *ΔCLI*) quintiles amount to about 20%–30% per month. This finding corroborates that the *ΔCLI* portfolios in Table 3 are associated with both dynamic portfolio rebalancing and reconstruction.

Finally, to provide additional insights into the issue of portfolio rotation, we conduct two further tests. First, we compute migration matrices of the quintile portfolios from Table 3 over different periods: from one month to 36 months. Second, we calculate rank-based Spearman correlation coefficients for the same time intervals. The results in Table A4 of the Internet Appendix provide further insight on the dynamics of the *ΔCLI* portfolios. The correlation between both the *ΔCLI* rankings and portfolio composition is relatively similar over the short term. Nonetheless, over time, the countries gradually migrate to different portfolios. Eventually, more than a year after the original portfolio formation, a positive correlation between subsequent country rankings can no longer be spotted.

3.2. Bivariate portfolio sorts

Although *ΔCLI* appears to be a reliable predictor of future returns, the relation could be confounded by other predictors of stock returns. To address this problem and ensure that *ΔCLI* contains independent and unique information about future stock performance, we next turn to bivariate portfolio sorts. Specifically, in each month, we first rank the markets on the set of control variables from Subsection 2.3 and group them into tertiles. Subsequently, within each of the control groups, we sort the markets into three *ΔCLI* tertiles. Finally, we compute the average mean returns across the *ΔCLI* tertiles to produce the portfolios with dispersion in *ΔCLI* but with a consistent level of control variables. As previously shown, we additionally form long-short portfolios by buying (selling) the high (low) *ΔCLI* markets. Lastly, we examine the spread portfolios with factor models. For the sake of brevity, we henceforth limit the presentation to the comprehensive 11-factor model only, as it nests all the other models we consider.

Table 5 displays the results of the two-way sorts based on ten control variables: *SIZE*, *VAL*, *SREV*, *MOM*, *LREV*, *IVOL*, *BETA*, *SKEW*, *SEAS*, and *CRED*. Noticeably, none of them subsumes *ΔCLI*: The effect of changes in the leading indicators remains significant, even after controlling for each of the predictors. The average differential returns and alphas remain sizeable and significant in all cases and for both the equal- and value-weighed portfolios. The average differential returns for the equal-weighted sorts span between 0.90% and 1.14%, while the corresponding range for the value-weighted portfolios is from 0.79% to 1.17%. This implies that the control variables can explain between 18% and 45% of the abnormal returns on the *ΔCLI* strategies.

3.3. Cross-sectional regressions

The sequential double-sort method used in Subsection 2.2 is a powerful non-parametric tool that assumes no functional form between the returns and variables and is highly robust to outliers. Nonetheless, it can hardly accommodate more than two or three return predictors. Furthermore, grouping assets into portfolios may lead to information loss. A feasible way to alleviate these concerns is to utilize more granular tests. Therefore, we now turn to the cross-sectional regressions in the style of Fama and MacBeth (1973).

That is, in each month, we cross-sectionally regress the stock returns on *ΔCLI* and a set of control variables:

$$R_i = \gamma_0 + \gamma_{\Delta CLI} \Delta CLI_i + \sum_{j=1}^{n} \gamma_{K,j} K_{i,j} + \varepsilon_i, \tag{3}$$

where R_i denotes the monthly return on the market index *i*, ΔCLI_i denotes the change in the local leading indicator, $K_{i,j}$ is the vector of the control variables outlined in Subsection 2.3, γ_0, $\gamma_{\Delta CLI}$, and $\gamma_{K,j}$ are the estimated regression coefficients, and ε_i denotes the error term. Note that *ΔCLI* and all the control variables have a built-in lag, so equation (3) can be interpreted as a predictive regression for

Table 3

Univariate portfolio sorts. The table reports the returns on quintile portfolios from one-way sorts on the change in the local leading indicator (*ΔCLI*). *High* and *Low* denote the quintiles with the highest and lowest *ΔCLI*, respectively. *High-Low* is the spread portfolio buying (selling) the *High* (*Low*) quintile. The portfolios are equal- or value-weighted (Panels A and B, respectively) and are rebalanced monthly. *R* is the mean monthly excess return and *Vol* is the standard deviation of excess returns. The table also reports the alphas from different factor models: the global CAPM (α_{CAPM}); three-factor models (α_{FF3}, α_{AMP}) in the style of Fama and French (1993) and Asness et al. (2013); four- and five-factor models (α_{CAR4}, α_{CAR5}) following Carhart (1997); and the comprehensive 11-factor model (α_{COMP}). All the returns, volatilities, and alphas are reported in percentage terms. The numbers in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) estimator. The sample covers 39 countries and the study period runs from February 1967 to March 2021.

	Panel A: Equal-weighted portfolios								Panel B: Value-weighted portfolios							
	R	Vol	α_{CAPM}	α_{FF3}	α_{CAR4}	α_{CAR5}	α_{AMP}	α_{COMP}	R	Vol	α_{CAPM}	α_{FF3}	α_{CAR4}	α_{CAR5}	α_{AMP}	α_{COMP}
Low ΔCLI	0.16	5.60	−0.34	−0.58	−0.54	−0.50	−0.38	−0.46	−0.01	5.38	−0.49	−0.57	−0.57	−0.55	−0.52	−0.49
	(0.59)		(−1.94)	(−3.34)	(−3.28)	(−3.11)	(−2.24)	(−3.37)	(−0.05)		(−3.36)	(−3.99)	(−4.06)	(−3.97)	(−3.66)	(−3.64)
2	0.40	5.01	−0.08	−0.18	−0.18	−0.18	−0.11	−0.19	0.40	5.16	−0.08	−0.14	−0.12	−0.12	−0.10	−0.13
	(1.77)		(−0.58)	(−1.44)	(−1.31)	(−1.27)	(−0.82)	(−1.48)	(1.90)		(−0.71)	(−1.18)	(−1.04)	(−1.01)	(−0.82)	(−1.04)
3	0.91	5.22	0.43	0.26	0.23	0.23	0.37	0.23	0.72	5.21	0.23	0.13	0.09	0.08	0.16	0.07
	(3.84)		(2.83)	(1.85)	(1.51)	(1.56)	(2.20)	(1.75)	(3.28)		(1.70)	(1.02)	(0.75)	(0.66)	(1.25)	(0.56)
4	0.89	5.04	0.43	0.28	0.29	0.27	0.42	0.27	0.70	5.01	0.23	0.14	0.09	0.08	0.15	0.12
	(3.86)		(3.11)	(2.19)	(2.22)	(2.13)	(3.02)	(2.22)	(3.25)		(2.02)	(1.30)	(0.84)	(0.77)	(1.35)	(1.20)
High ΔCLI	1.58	5.64	1.11	0.87	0.82	0.71	0.98	0.79	1.36	5.95	0.85	0.70	0.70	0.66	0.81	0.77
	(5.91)		(6.26)	(5.26)	(5.09)	(4.71)	(5.75)	(5.28)	(5.00)		(5.24)	(4.48)	(4.27)	(4.14)	(4.56)	(4.40)
High-Low	1.43	4.29	1.45	1.45	1.36	1.22	1.36	1.25	1.37	5.26	1.34	1.28	1.27	1.21	1.33	1.26
	(7.78)		(7.76)	(7.64)	(7.00)	(6.62)	(6.90)	(7.01)	(6.53)		(6.62)	(6.20)	(6.00)	(5.87)	(6.01)	(5.37)

Table 4
Composition of portfolios from one-way sorts. The table presents the composition of the portfolios from way sorts on the change in the local leading indicator (*ΔCLI*). *High* and *Low* denote the quintiles with the highest and lowest *ΔCLI*, respectively. Panel A presents the percentage of time a given country is included in the specific portfolio indicated in the top row. Panel B shows the average portfolio turnover calculated closely following Bollerslev et al. (2018) and Koijen et al. (2018), where the average share of a portfolio is replaced each month. All the reported values are in percentages. The sample covers 39 countries. The study period is from February 1967 to March 2021.

	Low *ΔCLI*	2	3	4	High *ΔCLI*
Panel A: Proportion of the time the country included in a given portfolio					
Australia	16.8	26.3	21.8	24.3	10.8
Austria	13.2	23.9	24.1	22.3	16.6
Belgium	14.6	18.8	26.6	27.7	12.3
Brazil	25.8	12.2	14.3	15.4	32.3
Canada	21.8	21.7	23.1	14.8	18.6
Chile	26.0	29.0	10.3	11.7	23.0
China	21.1	19.3	19.9	21.7	18.0
Czechia	28.8	16.3	9.3	16.3	29.2
Denmark	21.3	20.8	16.7	22.9	18.2
Estonia	34.1	9.3	8.3	9.7	38.6
Finland	21.8	18.1	18.8	21.3	20.1
France	14.2	25.2	26.3	23.4	10.9
Germany	19.2	19.8	21.1	18.6	21.2
Greece	21.3	20.9	20.2	17.9	19.8
Hungary	24.4	21.0	14.6	14.3	25.8
India	24.6	18.7	16.8	15.6	24.3
Indonesia	24.5	12.6	13.4	16.4	33.1
Ireland	25.4	13.5	17.8	16.7	26.5
Israel	17.9	21.5	20.2	20.8	19.6
Italy	21.2	18.9	21.7	17.5	20.7
Japan	23.7	17.2	17.2	18.5	23.4
Korea	31.7	11.8	11.8	18.0	26.6
Luxembourg	14.9	21.0	23.0	28.9	12.2
Mexico	30.7	14.8	12.4	11.8	30.3
the Netherlands	7.2	22.5	37.8	24.6	7.8
New Zealand	22.5	22.3	15.2	15.7	24.3
Norway	18.6	18.6	19.1	26.5	17.3
Poland	27.1	17.1	17.7	16.5	21.7
Portugal	22.1	19.3	17.3	18.6	22.6
Russia	23.2	15.2	12.1	22.9	26.7
Slovakia	23.9	14.4	13.3	16.1	32.2
Slovenia	34.5	6.7	8.6	13.1	37.1
South Africa	20.8	21.2	19.9	20.3	17.8
Spain	23.1	18.3	17.5	19.2	21.8
Sweden	21.6	21.2	17.2	18.0	22.1
Switzerland	19.2	19.8	21.4	20.0	19.5
Turkey	30.5	12.3	10.1	10.3	36.8
the United Kingdom	15.8	27.0	25.3	17.5	14.5
the United States	20.0	21.8	23.2	20.3	14.6
Panel B: Average portfolio turnover					
Equal-weighted	21.7	43.8	49.6	45.1	22.7
Value-weighted	30.0	51.3	55.6	53.4	33.6

future stock returns.

Table 6 reports the average slope coefficients for equation (3). Specification (1) presents the results of univariate tests with no control variables included. The average coefficient is positive and highly significant, confirming the robust cross-sectional link between *ΔCLI* and future stock returns. Specifications (2) to (11) are designed similarly to the bivariate sorts in Subsection 3.2: Each of them includes a control variable. Again, the estimated coefficient of *ΔCLI* remains highly significant and is not subsumed by any individual predictor. Finally, the rightmost column (Specification [12]) provides the results of the “kitchen-sink” approach, which simultaneously includes all the control variables. However, even in this approach, the predictive power of *ΔCLI* remains largely unaffected, with the slope coefficient’s *t*-statistic above 4. The coefficient of *ΔCLI* is 0.012, which implies that when the change in the local leading indicator increases cross-sectionally by one, the associated stock return soars on average, ceteris paribus, by 1.2%.

The univariate and bivariate sorts, as well as the cross-sectional regression, all indicate a strong positive relation between past changes of the leading macroeconomic indicator and country-level stock returns. The high *ΔCLI* markets visibly outperform their low *ΔCLI* counterparts. Crucially, the effect cannot be subsumed by an array of other return predictors, so it is unlikely to be another anomaly.

One of the potential weaknesses of cross-sectional regressions in the country-level context may be a relatively small asset universe.

Table 5
Bivariate portfolio sorts. The table reports the monthly returns on portfolios from two-way dependent sorts on the change in the local leading indicator (*ΔCLI*) and different control variables: market size (*SIZE*), dividend yield (*VAL*), short-term reversal (*SREV*), momentum (*MOM*), long-term reversal (*LREV*), idiosyncratic risk (*IVOL*), global market beta (*BETA*), skewness (*SKEW*), seasonality (*SEAS*), and credit risk (*CRED*). In the first step, the countries are sorted into tertiles based on one of the control variables. Next – within each of these subsets – we form the tertiles of countries with *Low*, *Medium*, and *High* levels of *ΔCLI*. The table displays the average mean returns across the three *ΔCLI* tertiles to produce the tertile portfolios with dispersion in *ΔCLI*, but with a consistent level of the control variables. *H-L R* represents the average return on the differential portfolios that buys (sells) the *High* (*Low*) tertile, and *H-L* α_{COMP} is the corresponding comprehensive model alpha. The portfolios are equal- or value-weighted (Panels A and B—respectively), and are rebalanced monthly. The returns and alphas are reported in percentages. The values in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) method. The sample covers 39 countries. The study period is from February 1967 to March 2021.

	Panel A: Equal-weighted portfolios					Panel B: Value-weighted portfolios				
	Low	Medium	High	H-L R	H-L α_{COMP}	Low	Medium	High	H-L R	H-L α_{COMP}
SIZE	0.34	0.71	1.39	1.05	0.95	0.29	0.71	1.28	0.99	0.96
	(1.40)	(3.10)	(5.60)	(7.67)	(7.01)	(1.25)	(3.13)	(5.25)	(6.81)	(6.33)
VAL	0.27	0.79	1.35	1.08	0.92	0.15	0.70	1.15	0.99	0.92
	(1.11)	(3.45)	(5.49)	(8.51)	(7.09)	(0.69)	(3.30)	(4.83)	(6.95)	(5.89)
SREV	0.28	0.87	1.32	1.04	0.98	0.20	0.70	1.11	0.91	0.90
	(1.17)	(3.78)	(5.47)	(8.69)	(8.06)	(0.87)	(3.20)	(4.91)	(7.04)	(6.16)
MOM	0.36	0.86	1.30	0.94	0.85	0.35	0.80	1.14	0.79	0.79
	(1.49)	(3.65)	(5.40)	(7.72)	(6.80)	(1.49)	(3.47)	(5.05)	(6.19)	(5.49)
LREV	0.36	0.79	1.26	0.90	0.76	0.31	0.72	1.10	0.79	0.75
	(1.47)	(3.50)	(5.10)	(7.14)	(6.09)	(1.37)	(3.36)	(4.70)	(5.92)	(5.28)
IVOL	0.40	0.69	1.33	0.93	0.76	0.24	0.67	1.15	0.91	0.80
	(1.64)	(2.93)	(5.51)	(7.28)	(5.95)	(1.00)	(2.94)	(4.87)	(6.09)	(4.98)
BETA	0.27	0.86	1.38	1.10	0.98	0.18	0.76	1.19	1.01	0.96
	(1.12)	(3.75)	(5.61)	(8.58)	(8.08)	(0.80)	(3.55)	(4.98)	(7.79)	(6.62)
SKEW	0.30	0.76	1.33	1.03	0.90	0.21	0.66	1.17	0.97	0.87
	(1.23)	(3.40)	(5.35)	(7.69)	(6.61)	(0.90)	(3.09)	(4.91)	(6.51)	(5.46)
SEAS	0.30	0.76	1.20	0.90	0.72	0.26	0.70	1.19	0.93	0.84
	(1.31)	(3.27)	(5.12)	(7.92)	(6.25)	(1.22)	(3.08)	(5.13)	(7.08)	(6.10)
CRED	0.24	0.80	1.38	1.14	1.00	0.08	0.68	1.25	1.17	1.08
	(1.00)	(3.45)	(5.37)	(8.15)	(7.54)	(0.37)	(3.13)	(5.12)	(8.32)	(7.87)

When combined with many explanatory variables, this may result in a small number of degrees of freedom. Hence, in certain cases, panel data regressions may be preferable. To assure that our results hold in this framework as well, we reproduce the tests in Table 6 using panel regressions. Specifically, we employ pooled OLS and fixed effects models and calculate *t*-statistics based on the two-way cluster-robust standard errors (Cameron et al., 2011; Thompson, 2011). The results in Table A5 in the Internet Appendix are qualitatively consistent with the conclusions from the cross-sectional regressions: *ΔCLI* still remains a robust predictor of future returns.

4. Further insights and robustness checks

4.1. Modified trading signals and portfolio designs

In this subsection, we discuss further robustness checks and additional analyses To start, we embark on alternative trading signal and portfolio construction methods.

The CLI values are sometimes subject to revisions following the first publication. As a rule, during the initial aggregation process, the OECD applies a 60% threshold on component availability. Consequently, the CLI is released even if some contributing series are not available at the time of initial publication, as only 60% of them are required. The component availability typically improves in the next publication. Furthermore, CLI can be revised if some of its underlying components require revision.

Nilsson and Guidetti (2007) demonstrate that, although the initial CLI releases are revised quite frequently, the magnitude of these adjustments is usually small. Nevertheless, to guard against the risk of look-ahead bias, we introduce two modifications to our baseline *ΔCLI* calculation in equation (1). First, we apply additional one- and two-month skipping periods between the *ΔCLI* calculation and the forecast periods. In other words, we predict the returns in month *t* based on the CLI changes in months *t*-3 or *t*-4 (instead of *t*-2), as seen in equation (1). Second, we extend the *ΔCLI* estimation period, from one month to three, six, or 12 months.

Panel A in Table 7 reports the performance of the equal-weighted long-short quintile portfolios based on the modified *ΔCLI* measures. Our findings remain qualitatively robust to these modifications. Concerning the extra skipping periods, their inclusion indeed reduces the magnitude of the abnormal returns. Nevertheless, even if an additional lag of two months is applied, the spread portfolio still produces an average monthly return of 0.81% (*t*-stat, = 4.94). Analogously, profits of the long-short strategy gradually decline, along with the extended measurement period. The anomaly is still comparably high and significant for the six-month formation period, yielding mean monthly returns of 0.88% (*t*-stat, = 5.04). For the 12-month CLI change, however, the mean differential return drops to 0.53% (*t*-stat. = 2.50) and the corresponding alpha is 0.34% (*t*-stat. = 1.65). The weakening anomaly, when measured with longer periods, may also be a sign of gradual information diffusion. Once investors fully discount the new economic conditions,

Table 6
Cross-sectional regressions. The table reports the average slope coefficients from the following cross-sectional regressions in the style of Fama and MacBeth (1973): $R_i = \gamma_0 + \gamma_{\Delta LI} \Delta CLI_i + \sum_{j=1}^{n} \gamma_{K,j} K_{j,i} + \varepsilon_i$,

where R_i denotes the monthly return on the stock index i, ΔCLI_i denotes the change in the local leading indicator, and $K_{i,j}$ is the vector of possible control variables; including market size (*SIZE*), dividend yield (*VAL*), short-term reversal (*SREV*), momentum (*MOM*), long-term reversal (*LREV*), idiosyncratic risk (*IVOL*), global market beta (*BETA*), skewness (*SKEW*), seasonality (*SEAS*), and credit risk (*CRED*)., $\gamma_{\Delta LI}, \gamma_0$ and $\gamma_{K,j}$ are the estimated regression coefficients, and ε_i denotes the error term. The values in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) estimator. $\overline{R^2}$ is the average cross-sectional adjusted coefficient of determination and *#Obs*. Indicates the number of country-month of observations. The sample covers 39 countries. The study period is from February 1967 to March 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔCLI	0.015	0.015	0.014	0.013	0.013	0.014	0.015	0.014	0.014	0.012	0.015	0.012
	(7.51)	(7.08)	(7.67)	(7.27)	(7.10)	(7.49)	(7.61)	(7.18)	(7.23)	(6.42)	(7.37)	(4.02)
SIZE		−0.001										−0.001
		(-2.71)										(-1.81)
VAL			0.084									0.058
			(3.55)									(2.07)
SREV				0.045								−0.023
				(3.29)								(-0.70)
MOM					0.103							0.009
					(2.12)							(0.11)
LREV						−0.182						−0.423
						(-2.35)						(-2.61)
BETA							0.003					0.001
							(1.43)					(0.33)
SKEW								0.001				−0.003
								(0.92)				(-1.23)
IVOL									0.079			0.097
									(2.26)			(1.02)
SEAS										0.034		0.230
										(0.66)		(2.46)
CRED											0.000	0.001
											(-0.41)	(1.02)
$\overline{R^2}$	0.064	0.162	0.232	0.287	0.333	0.381	0.438	0.444	0.435	0.500	0.423	0.695
#Obs.	18,704	18,651	18,526	18,695	18,686	18,568	18,686	18,252	18,686	15,013	17,971	14,022

the abnormal returns visibly attenuate.

Panel B of Table 7 provides the results of alternative portfolio construction methods. To reiterate, our baseline approach in Subsection 3.1 assumes equal- and value-weighted quintiles. Now, we relax these assumptions in two ways. First, we consider two alternative weighting methods: 1) risk-parity portfolios, where the allocation of capital to different markets is based on their inverse volatility measured over the past 36 months; and 2) rank-weighted portfolios, which weight components on their de-meaned *ΔCLI* rank (as in Asness et al., 2013). Furthermore, we want to ensure that the strategy performance is not sensitive to the choice of the cutoff

Table 7
Alternative trading signals and portfolio formation methods The table presents the returns on spread portfolios formed on the change in the local leading indicator (*ΔCLI*) that is formed using alternative trading signals and portfolio formation methods. The portfolios in Panel A buy (sell) an equal-weighted quintile of markets with the highest (lowest) change in LI, computed over different periods. The portfolios in Panel B assume modified breakpoints and weighting methods. The details of the methodological modifications are described in Subsection 4.1. All portfolios are rebalanced monthly. *R* denotes the mean monthly return, and α_{COMP} denotes the corresponding comprehensive model alpha, both are reported in percentage terms. The values in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) estimator. The sample covers 39 countries. The study period is from February 1967 to March 2021.

	R	$t\text{-}stat_R$	α_{COMP}	$t\text{-}stat_\alpha$
Panel A: Modified trading signals				
One-month skip period	1.11	(6.15)	0.93	(5.35)
Two-month skip period	0.81	(4.94)	0.66	(4.14)
Two-month LI change	1.24	(7.07)	1.06	(6.25)
Three-month LI change	1.20	(6.74)	1.01	(5.97)
Six-month LI change	0.88	(5.04)	0.69	(4.28)
Twelve-month LI change	0.53	(2.50)	0.34	(1.65)
Panel B: Alternative portfolio construction methods				
Risk-parity portfolios	1.38	(8.34)	1.17	(7.22)
Rank weighted portfolios	1.17	(8.45)	1.03	(7.83)
Quartile portfolios	1.34	(8.50)	1.19	(7.80)
Sextile portfolios	1.52	(8.00)	1.41	(7.63)

point. Therefore, instead of quintiles, we adopt quartiles and sextiles to form the spread portfolios, respectively. However, none of these operations have a qualitative impact on our conclusions. The long-short *ΔCLI* strategies continue to produce positive and significant abnormal returns.

4.2. Local currency returns

Although the international asset pricing studies typically rely on stock returns denominated in U.S. dollars, the validity of the global CAPM relies on the purchasing power parity assumption and international market integration (see Solnik, 1974a, b). Nevertheless, some studies cast doubt on this conjecture, even in the context of developed markets (Ferson and Harvey, 1993, 1994; Dumas and Solnik, 1995). If the full integration assumption is invalid, then the local currency returns may matter (see Hou et al., 2011). Therefore, to account for this issue, we repeat the analysis but using local currency returns. This additional experiment allows us to disentangle the influence of *ΔCLI* on the stock markets from the interference of currency conversion.

We reproduce our original univariate sorts (Table 3) and cross-sectional regressions (Table 6) in Tables A6 and A7 in the Internet Appendix. We repeat the previous procedures with one modification only: the USD-denominated market returns are replaced with local currency returns. The results of both analyses validate our baseline findings: the *ΔCLI* significantly predicts future stock returns, regardless of the FX conversion, and the effect holds for the local currency returns as well.

4.3. Local pricing factors

Our baseline approach focuses on testing portfolios with global factors derived from country-level data, ensuring that both left-hand side and right-hand side portfolios are derived from identical asset universes. Nonetheless, Hou et al. (2011) and Lewis (2011) also accentuate the role of local pricing factors. Hence, we perform additional tests using factors derived from stock-level data.

In these tests, we evaluate the performance of the long-short *ΔCLI* portfolios outlined in Subsection 2.1 with a set of well-known asset pricing factors derived from firm-level data. We consider ten different models: the CAPM; Fama and French's (1992, 1992, 2015, 2018) three-, five-, and six-factor models; Carhart's (1997) four-factor model; the *q*-model and augmented *q*-model of Hou et al. (2015, 2021); the mispricing factors model of Stambaugh and Yuan (2017); the behavioral model of Daniel et al. (2020); and Barillas and Shanken's (2018) six-factor model. The details of the factors used in these tests are in Table A8 in the Internet Appendix.

The results are in Table A9 in the Internet Appendix. The results indicate that the stock-level models are not enough to explain the *ΔCLI* effect. The alphas remain positive, sizeable, and significant across all the models and weighting schemes. Our main conclusions regarding the stock return predictability by *ΔCLI* continue to hold.

4.4. Subsample analysis

To investigate whether the *ΔCLI* effect is present in the broad cross-section of international equity indices, we conduct an extensive subsample analysis. Specifically, we split the main sample into halves based on different variables from the asset pricing literature. Within each of these subsamples, we form the quintile portfolios from one-way sorts on *ΔCLI* (as for Table 3).

We use 19 different variables to divide the main sample, with the details provided in Table A10 in the Internet Appendix. We group the variables into several major categories. First, studies document that the magnitude of mispricing may depend on various dimensions of culture, such as collectivism or myopia (e.g., Chui et al., 2010; Cheon and Lee, 2018). To account for this, we split the sample by the six cultural traits considered in Hofstede (2001) and Hofstede et al. (2005): power distance (*PDI*), individualism (*IND*), masculinity (*MSC*), uncertainty avoidance (*UNC*), long-term orientation (*LTO*), and indulgence (*ILG*).

Second, according to the behavioral interpretation, market anomalies should be stronger in assets associated with higher limits to arbitrage (Shleifer and Vishny, 1997). Hence, building primarily on Lam and Wei (2011) and Watanabe et al. (2013), we classify the markets based on their market value (*MV*), average dollar volume (*DVOL*), idiosyncratic risk (*IRISK*), and Amihud's (2002) illiquidity ratio (*ILLIQ*). Third, Jacobs (2016) accentuates the essential role of market development. In this spirit, we categorize the countries by the future earnings response coefficient (*FERC*), aggregate market importance measure (*MKT*) of Watanabe et al. (2013), and legal origin (*LAW*). We also incorporate a developed market indicator (*DEV*), as in Azevedo and Müller (2020).

Last, Watanabe et al. (2013) and Hollstein and Sejdiu (2020) indicate that the limits to arbitrage may also be linked with shareholder protection. Therefore, to account for this issue, we split the sample by five different variables: credit rights index (*CR*) and accounting standard (*ACCD*) indices adopted from La Porta et al. (1998); anti-director rights (*AD*) and anti-self-dealing indices (*AS*) by Djankov et al. (2008); and earnings management score (*EMS*), originating from Leuz et al. (2003). The essential statistical properties of all of these measures are summarized in Table A11 in the Internet Appendix.

Table A12 in the Internet Appendix reports the results of the subsample analysis. In all the different market segments, the *ΔCLI* effect is strong and robust, confirming that it does not originate from some small or illiquid markets. In fact, we find some heterogeneity associated with certain variables. For example, mispricing is relatively stronger in markets characterized by higher idiosyncratic risk. Interestingly, this is consistent with the findings of McLean (2010) and Akbas et al. (2016), among others, who link this feature with limits to arbitrage. Overall, the *ΔCLI* spread portfolios continue to produce positive mean returns and alphas across all the different market segments.

4.5. Performance in subperiods

We are also interested in the time variation of the ΔCLI effect. The asset pricing literature emphasizes a lack of stability in the magnitude of mispricing, linking the dynamics with different economic phenomena. In Figure A1 in the Internet Appendix, we plot the cumulative returns on the spread portfolios that buy (sell) the quintile of markets with the highest (lowest) ΔCLI values. The exhibit does not reveal apparent substantial time variation. Indeed, we can spot certain periods of augmented anomaly returns (such as the years 1998–2001), but the overall performance is rather stable. Nonetheless, to explore this issue further, we conduct a more in-depth subperiod analysis.

In this exercise, we divide the full study period into various subperiods and check the performance of the corresponding long-short ΔCLI portfolios therein. To assure robustness, we employ a range of different splits. Several recent studies argue that anomaly profits attenuated in the past due to investor learning and the improvement in market efficiency (e.g., Chordia et al., 2014; McLean and Pontiff, 2016). Hence, we divide the sample into halves (January 1967 to February 1994 and March 1994 to March 2021) and examine portfolio performance within the 20th and 21st centuries separately. Furthermore, because certain anomalies tend to be influenced by the January seasonality, we reproduce our analysis by excluding these specific periods from our sample.

In further subperiod tests, we divide the entire study period into halves by the median of assorted control variables. The detailed descriptions of these measures, as well as their statistical properties, are in Tables A13 and A14 in the Internet Appendix. For the sake of conciseness, we only provide a brief overview here.

First, the dynamics of some anomalies tend to depend on market states. Specifically, they may differ in bull, bear, volatile, stable, and dispersed markets (e.g., Connolly and Stivers, 2003; Cooper et al., 2004; Jacobs, 2015). For that reason, we split the study period by the median return dispersion, valuation measured with the global P/E ratio, the average idiosyncratic risk, the global market volatility (volatile vs. stable markets), the contemporaneous market return (up vs. down markets), and the past long-run return (bull vs. bear markets).

Second, we consider time-varying funding and trading liquidity as one of the driving forces of limits to arbitrage. Hence, we control for two proxies of market liquidity: average global Amihud's (2002) illiquidity measure and average turnover. We also account for several measures that may affect the cost and availability of financing: T-bill rate, TED spread, term spread, and corporate credit spread.

Third, motivated by Stambaugh et al. (2012), who document the connection between investor sentiment and mispricing, we control for two different sentiment measures: the Baker and Wurgler (2006) index and the consumer confidence indicator. Fourth, we incorporate different macroeconomic regimes. Specifically, we check the portfolio returns during periods of both high and low global GDP growth and inflation rates. Finally, we use the measures of Baker et al. (2016) and Caldara and Iacoviello (2018) to partition the sample based on the global geopolitical risk and economic uncertainty.

Table A15 in the Internet Appendix reports the results of the subperiod analysis. The performance of the ΔCLI portfolios is remarkably stable, though it partly attenuates over time. The average monthly spread portfolio return in the 20th century was as high as 1.91% per month, while in the 21st century, it declined to 0.68%.

Importantly, the long-short ΔCLI strategy returns in Table A15 are both positive and significant across all the subperiods. Nevertheless, some differences in the magnitude of mispricing can be spotted. For example, the ΔCLI portfolio returns are higher during periods when the cost of short-term financing is high (i.e., elevated T-bill rates and TED spreads). Furthermore, the abnormal returns tend to also be augmented by high market dispersion and idiosyncratic risk. These findings are consistent with the behavioral mispricing story of ΔCLI and emphasize the amplified anomaly during times of more acute limits to arbitrage.

4.6. Alternative explanations

Our baseline story attributes the ΔCLI effect to investors' underreaction to predicted changes in the economic environment. Nevertheless, the observed phenomenon may also be driven by alternative economic mechanisms based on the current findings. To further unveil the underlying mechanism, we next run additional tests to rule out these alternatives.

Hjalmarsson (2010) argues that a favorable interest rates environment (e.g., level, yield curve slope) can boost future equity returns. Furthermore, Zaremba et al. (2021) and Pitkäjärvi et al. (2020), demonstrate the critical role of bond market dynamics. Theoretically, the phenomenon we observe may stem from either low or falling interest rates, which supports future firm performance. To verify this conjecture, we include three additional controls: local 3-month T-bill rate at month t-1; the slope of the yield at t-1, calculated as the difference between the 10-year Treasury bond yield and the 3-month T-bill rate; and the change in the 10-year government bond yield over the last 12 months (t-12 to t-1). We obtain the bond market data from GFD.

The ΔCLI effect may also be driven by the state or change in the contemporaneous economic environment rather than by expectations. Hence, we control for the most essential economic indicators: the last available annual GDP growth, unemployment rate, and inflation rate. Furthermore, Brooks (2017) argues that not only does the current state of the economy matter, but also its past dynamics. He shows that macroeconomic momentum spillover to equities drives international stock returns in the cross-section. To account for this, we compute a 12-month change in the averaged z-score associated with the three indicators mentioned above: GDP growth, inflation, and unemployment rate.[11] Finally, Wisniewski and Jackson (2020) show that growth in local government debt also

[11] We multiply the inflation and unemployment rate by −1 to ensure that for all the variables, a higher z-score indicates a better economic situation.

Table 8
Tests of alternative explanations The table presents the results of the alternative hypothesis tests, explaining the leading indicator effect based on two-way dependent portfolio sorts. The portfolios come from bivariate sorts on the change in the local leading indicator (*ΔCLI*) and various variables representing alternative explanations, as outlined in detail in Subsection 4.6. In the first step, the countries are sorted into tertiles based on one of the control variables. Next, within each of these subsets, we form the tertiles of countries with *Low*, *Medium*, and *High* levels of *ΔCLI*. The table displays the average mean returns across the 10 *ΔCLI* tertiles to produce the tertile portfolios with dispersion in *ΔCLI*, but with a consistent level of the control variables. *H-L R* represents the average return on the differential portfolios that buys (sells) the *High* (*Low*) tertile, and *H-L α* is the corresponding comprehensive model alpha. The portfolios are equal- or value-weighted (Panels A and B—respectively) and are rebalanced monthly. The returns and alphas are reported in percentages. The values in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) method. The sample covers 39 countries. The study period is from February 1967 to March 2021.

	Panel A: Equal-weighted portfolios					Panel B: Value-weighted portfolios				
	Low	Medium	High	H-L R	H-L α	Low	Medium	High	H-L R	H-L α
T-bill yield	0.55	0.86	1.30	0.75	0.63	0.36	0.77	1.32	0.96	0.89
	(2.52)	(4.09)	(5.53)	(5.46)	(4.10)	(1.72)	(3.72)	(5.60)	(6.02)	(5.29)
Yield curve slope	0.32	0.67	1.10	0.77	0.76	0.27	0.65	0.95	0.69	0.72
	(1.59)	(3.28)	(5.09)	(6.68)	(6.01)	(1.37)	(3.28)	(4.52)	(6.17)	(6.04)
Bond yield momentum	0.31	0.66	1.09	0.79	0.72	0.32	0.59	0.96	0.64	0.71
	(1.56)	(3.34)	(5.15)	(6.86)	(5.73)	(1.63)	(3.02)	(4.40)	(4.83)	(4.95)
Change in gov. Debt	0.59	0.80	1.48	0.89	0.76	0.42	0.65	1.28	0.87	0.87
	(2.70)	(3.84)	(6.04)	(6.05)	(5.87)	(1.87)	(3.26)	(5.46)	(4.66)	(5.38)
GDP growth	0.65	0.94	1.63	0.98	1.00	0.43	0.73	1.38	0.95	1.05
	(2.60)	(3.98)	(6.16)	(5.84)	(7.23)	(1.91)	(3.26)	(5.57)	(5.39)	(6.79)
Inflation rate	0.57	0.78	1.53	0.96	0.82	0.48	0.69	1.50	1.02	0.94
	(2.52)	(3.74)	(6.42)	(6.80)	(6.20)	(2.05)	(3.29)	(6.12)	(5.62)	(6.00)
Unemployment rate	0.54	0.64	1.31	0.77	0.77	0.35	0.54	1.13	0.78	0.88
	(2.48)	(3.00)	(6.03)	(5.41)	(6.03)	(1.79)	(2.66)	(5.46)	(5.90)	(6.16)
Macro-momentum	0.63	0.70	1.48	0.85	0.63	0.57	0.52	1.28	0.71	0.83
	(2.68)	(3.13)	(6.11)	(5.53)	(4.10)	(2.46)	(2.43)	(5.61)	(4.22)	(5.61)
Control of corruption	0.61	0.77	1.44	0.83	0.76	0.46	0.69	1.19	0.72	0.81
	(2.74)	(3.63)	(6.32)	(6.16)	(6.01)	(2.13)	(3.28)	(5.29)	(4.22)	(6.36)
Gov. Effectiveness	0.61	0.81	1.40	0.79	0.72	0.36	0.70	1.16	0.81	0.74
	(2.72)	(3.77)	(6.30)	(6.23)	(5.73)	(1.68)	(3.35)	(5.18)	(5.18)	(5.82)
Political stability	0.52	0.92	1.43	0.91	0.76	0.31	0.87	1.17	0.86	0.91
	(2.29)	(4.43)	(6.25)	(6.57)	(5.87)	(1.45)	(4.19)	(5.34)	(5.27)	(7.09)
Regulatory quality	0.64	0.72	1.44	0.81	1.00	0.44	0.70	1.13	0.69	0.8
	(2.87)	(3.39)	(6.30)	(6.12)	(7.23)	(2.17)	(3.39)	(4.97)	(4.19)	(6.38)
Rule of law	0.64	0.78	1.41	0.78	0.82	0.45	0.71	1.18	0.74	0.74
	(2.84)	(3.61)	(6.26)	(5.67)	(6.20)	(2.02)	(3.28)	(5.47)	(4.28)	(5.81)
Voice and account	0.61	0.82	1.41	0.80	0.77	0.30	0.78	1.14	0.84	0.79
	(2.70)	(3.96)	(6.28)	(6.32)	(6.03)	(1.46)	(3.91)	(5.30)	(5.56)	(6.70)

matters. Building on this, we additionally incorporate a variable representing a 12-month change in the government debt to GDP level. Again, we acquire all the related economic data from GFD.

Last, previous studies link international stock returns to the political situation and regime. For example, Erb et al. (1996) and Dimic et al. (2015), among others, note that political risk is priced in the equity markets. Lehkonen and Heimonen (2015) and Lei and Wisniewski (2018), explore the role of democracy on stock returns. In addition, Narayan et al. (2015), Khan (2019), and Marshall et al. (2021) accentuate the importance of state-level corporate governance. Therefore, a potential confounder here is that the *ΔCLI* effect may stem from the state of the political environment partially reflected by the leading economic indicators. To scrutinize such a possibility, we examine the role of the six World Governance Indicators (WGI) that are available from the World Bank: control of corruption, government effectiveness, political stability, regulatory quality, the rule of law, and voice and accountability.[12]

To investigate the role of the hypothesis outlined above, we employ the associated measures to perform bivariate sorts in the spirit of Subsection 3.2.[13] In each month, we group markets into tertiles based on these extra control variables, and then sort them into tertiles within each of the control groups. Finally, we calculate the average returns on the *ΔCLI* portfolios within each of the control deciles.

The results in Table 8 show that none of the alternative hypotheses explains the *ΔCLI* effect well. The mean returns and alphas on the spread portfolios formed on *ΔCLI* remain positive and significant in all cases. This observation holds for both equal- and value-weighted portfolios. To sum up, the *ΔCLI* phenomenon remains powerful, even after accounting for these alternative explanations. Thus, the *ΔCLI* effect is likely to be driven by underreaction to predicted changes in the economic environment instead of other alternative explanations.

[12] For the source data and detailed description, see https://info.worldbank.org/governance/wgi/. The WIG indicators are published annually or biannually. When data are unavailable, we backfill the gaps with the most recent observation. Furthermore, we splice the missing data in early years with the first available observation.

[13] Table A16 in the Internet Appendix provides statistical properties of the variables used in Subsection 4.6.

Table 9
Mean-variance portfolio analysis The table presents the maximum ex-post Sharpe ratios on portfolios that are composed of different country-level factors and the long-short ΔCLI strategies. The analyzed factor portfolios include the market (MKT^F), size ($SIZE^F$), value (VAL^F), momentum (MOM^F), short-term reversal ($SREV^F$), long-term reversal ($LREV^F$), idiosyncratic volatility ($IVOL^F$), skewness ($SKEW^F$), seasonality ($SEAS^F$), credit risk ($CRED^F$), and beta ($BETA^F$) factors. The ΔCLI spread portfolio buys (sells) a quintile of markets with the highest (lowest) ΔCLI. The first column indicates the factor model corresponding with the factor set used in different tests: the capital asset pricing model (CAPM), the augmented Carhart's (1997) four-factor model, and the comprehensive 11-factor model (COMP). All the portfolios (factors and ΔCLI strategies) in Panel A are equal-weighted, and Panel B reports the results for value-weighted portfolios. The left section of the table presents the weights assigned to different factors and strategies in the optimization process. SR denotes the maximum ex-post Sharpe ratio (on an annualized basis), and *LW* indicates the *p*-values from Ledoit and Wolf's (2008) test of Sharpe ratio equality for the portfolios including and excluding the ΔCLI strategy. The total sample covers 39 countries. The study period is from February 1967 to March 2021.

Factor set	Portfolio weights												Sharpe ratios	
	MKT^F	$SIZE^F$	VAL^F	MOM^F	$SREV^F$	$LREV^F$	$IVOL^F$	$SKEW^F$	$SEAS^F$	$CRED^F$	$BETA^F$	ΔCLI	SR	LW
Panel A: Equal-weighted portfolios														
CAPM	100.0%												0.40	0.0000
CAPM + ΔCLI	27.7%											72.3%	1.24	
CAR5	23.0%	17.9%	18.6%	18.5%	22.0%								1.53	0.0014
CAR5 + ΔCLI	19.6%	15.1%	15.3%	14.3%	14.7%							21.0%	1.82	
COMP	22.1%	19.5%	15.7%	17.8%	21.2%	11.3%	−5.9%	−2.5%	4.2%	−4.8%	1.4%		1.60	0.0010
COMP + ΔCLI	18.9%	17.2%	12.1%	13.3%	13.8%	8.8%	−6.7%	−1.4%	6.9%	−6.7%	2.2%	21.7%	1.91	
Panel B: Value-weighted portfolios														
CAPM	100.0%												0.40	0.0003
CAPM + ΔCLI	34.0%											66.0%	0.97	
CAR5	35.2%	31.0%	5.9%	14.9%	13.0%								0.76	0.0048
CAR5 + ΔCLI	24.6%	20.7%	5.7%	12.4%	2.5%							34.0%	1.12	
COMP	22.4%	17.9%	2.5%	9.3%	8.2%	10.0%	−8.9%	11.2%	8.5%	−1.1%	19.9%		0.96	0.0164
COMP + ΔCLI	15.2%	10.5%	3.5%	8.0%	0.0%	7.9%	−9.2%	9.6%	8.5%	−5.5%	18.8%	32.6%	1.28	

Table 10
Implementation in exchange-traded funds. The table exhibits the performance of portfolios of single-country exchange-traded funds (ETFs) that are formed on the change in the local leading indicators (*ΔCLI*). *High* and *Low* portfolios contain the tertile, quartile, or quintile (as indicated in the top row) of ETFs associated with the countries with the top and bottom value of *ΔCLI*—respectively. *H-L* is the differential return on a spread strategy buying (selling) the *High* (*Low*) portfolio. The portfolios are equal- or value-weighted (Panels A and B—respectively) and are rebalanced monthly. *R* is the mean monthly excess return, *Vol* is the portfolio return volatility, and *SR* denotes the annualized Sharpe ratio. *TURN* represents the mean monthly portfolio turnover, which is calculated following Bollerslev et al. (2018) and Koijen et al. (2018) as the average proportion of the portfolio that is replaced every month. *COST* is the breakeven trading cost. α_{CAPM} and α_{COPM} are the monthly alphas from the CAPM and comprehensive model—respectively. *R*, *Vol*, *TURN*, *COST*, α_{CAPM}, and α_{COPM} are presented in percentage terms. The values in parentheses are *t*-statistics adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) method. The sample covers 30 single-country ETFs. The study period is from March 1996 to March 2021.

	Tercile portfolios			Quartile portfolios			Quintile portfolios		
	Low	High	H-L	Low	High	H-L	Low	High	H-L
Panel A: Equal-weighted portfolios									
R	0.36	0.86	0.50	0.31	0.88	0.57	0.19	0.93	0.74
	(1.01)	(2.46)	(3.67)	(0.83)	(2.51)	(3.70)	(0.50)	(2.53)	(3.68)
Vol	5.71	5.71	2.47	5.81	5.81	2.71	5.97	5.96	3.22
SR	0.22	0.52	0.70	0.18	0.52	0.73	0.11	0.54	0.80
TURN	10.75	11.15	21.90	12.35	12.64	24.99	14.19	14.12	28.31
COST	1.67	3.86	1.14	1.26	3.48	1.14	0.67	3.29	1.31
α_{CAPM}	0.08	0.59	0.51	0.02	0.60	0.58	−0.10	0.64	0.75
	(0.43)	(2.60)	(3.71)	(0.09)	(2.53)	(3.74)	(-0.51)	(2.62)	(3.67)
α_{COPM}	−0.07	0.52	0.60	−0.14	0.53	0.68	−0.26	0.57	0.83
	(-0.36)	(2.19)	(4.10)	(-0.65)	(2.07)	(3.65)	(-1.12)	(2.13)	(3.46)
Panel B: Value-weighted portfolios									
R	0.08	0.92	0.84	0.02	0.92	0.91	−0.02	0.95	0.97
	(0.20)	(2.58)	(2.74)	(0.04)	(2.70)	(2.96)	(-0.04)	(2.62)	(3.00)
Vol	5.95	5.71	4.72	6.24	5.83	4.90	6.57	6.14	5.19
SR	0.05	0.56	0.62	0.01	0.55	0.64	−0.01	0.54	0.65
TURN	15.31	15.79	31.10	16.10	17.55	33.65	18.02	19.28	37.30
COST	0.26	2.91	1.35	0.06	2.62	1.35	−0.06	2.46	1.30
α_{CAPM}	−0.22	0.65	0.87	−0.29	0.65	0.94	−0.33	0.68	1.01
	(-1.14)	(2.82)	(2.87)	(-1.45)	(2.87)	(3.17)	(-1.60)	(2.79)	(3.21)
α_{COPM}	−0.40	0.60	1.00	−0.48	0.57	1.05	−0.53	0.62	1.14
	(-1.97)	(2.80)	(3.11)	(-2.21)	(2.42)	(3.21)	(-2.26)	(2.53)	(3.42)

5. Practical investor's perspective

5.1. Portfolio considerations

Our results indicate that the *ΔCLI* effect constitutes a reliable phenomenon that drives the cross-section of international stock returns. Can it be, therefore, successfully employed by equity investors? In addition, can it be coined into an efficient country selection strategy that adds value to a diversified global factor portfolio? To scrutinize these issues, we examine ex post Sharpe ratios.

The decision of whether or not to incorporate a new strategy in a portfolio depends not only on its risk-return profile but also on the co-movement with other strategies the investor pursues. Indeed, the correlation between the *ΔCLI* and other factors is relatively weak (see Table A17 in the Internet Appendix), making it a potentially valuable addition from investors' perspective. We next examine the incremental benefit of the *ΔCLI* strategies in a portfolio context. We follow the approach in Keloharju et al. (2016), who build on the framework of Gibbons et al. (1989) and investigate *ΔCLI*'s ability to improve the overall risk-return profile of a fully diversified portfolio that consists of many strategies.

We compute the maximum ex post Sharpe ratios for different groups of factor strategies, including and excluding the *ΔCLI* spread portfolios. We consider three different sets of factor strategies: 1) MKT^F only; 2) MKT^F, SIZE^F, VAL^F, MOM^F, and $SREV^F$, which correspond to the CAR5 model and reflect the most recognizable factor strategies; and 3) all 11 factors covered by the COMP model. We blend these sets of factors together and add the long-short *ΔCLI* strategies from Subsection 3.1. Finally, we verify whether the inclusion of the long-short *ΔCLI* strategies leads to a measurable improvement of the Sharpe ratio using the statistic of Ledoit and Wolf (2008).

Table 9 presents the results for the investor who rationally allocates capital to different factor sets. Notably, the portfolio optimizer always assigns a substantial proportion of the portfolio to the *ΔCLI* strategy. This share ranges between 21.0% and 72.3%, depending on the available factor set and weighting scheme.

The inclusion of the *ΔCLI* strategy in each of the cases leads to a substantial improvement in the ex-post Sharpe ratio. Even when all the other 11 factors are included, the Sharpe ratios still increase, reaching 1.91 (1.28) in the equal-weighted (value-weighted) framework. The significant rise of the point estimates is confirmed by the tests of Ledoit and Wolf (2008).

To conclude, the *ΔCLI* strategies can efficiently enhance the efficient frontier of an international investor, which is not restricted to unsophisticated market participants that passively track the market portfolio or follow simple strategies. The *ΔCLI* investment adds value, even in a highly multidimensional framework when a portfolio manager already pursues a broad array of assorted factors.

5.2. Implementation with exchange-traded funds

Studies on international risk premia, including ours, typically focus on single-country equity indices. Although this approach assures a broad and long sample, its practical implications may be a restriction. Nevertheless, investors are often not able to move their funds seamlessly and cheaply across countries, especially in emerging markets. The challenges may take a form not only of limited liquidity but also of institutional barriers, technical difficulties, or explicit capital mobility constraints. Hence, harvesting the ΔCLI premium may be quite difficult in practice. Therefore, to explore whether the ΔCLI effect may be exploited in an investable environment, we further investigate its implementation with exchange-traded funds (ETFs), which are often more accessible for most investors. This additional analysis is based on market and return data on single-country ETFs that were obtained from Datastream. We focus on the ETFs offered by iShares, which currently provides the broadest international coverage. To assure direct investability and get away from technical trading difficulties, we concentrate on the securities listed in the U.S. with prices quoted in U.S. dollars. The relevant iShares ETFs are available for 30 countries in our sample, most of which are developed. ETFs are relatively young instruments, so our study period is from January 1996 to March 2021. The results are in Table A18 in the Internet Appendix.

We form equal- and value-weighted portfolios containing 20%, 25%, or 30% of ETFs with the highest and lowest ΔCLI levels. As in Subsection 3.1, we also calculate long-short portfolios taking a long (short) position in the top (bottom) ΔCLI countries. We calculate a set of basic performance statistics, including Sharpe ratios and alphas. We also consider portfolio turnover, which is the critical driver of transaction costs. The results are in Table 10.

The ΔCLI effect drives the prices of single-country ETFs. Depending on the particular portfolio specification, the high ΔCLI securities outperform their low ΔCLI counterparts by between 0.50% and 0.97%. The long-short strategy returns generally grow along with the ΔCLI spread between the top and bottom deciles and are higher for the value-weighted portfolios than for the equal-weighted portfolios. Notably, the pattern is again not explained by common risk factors, so the spread portfolios continue to produce abnormal returns, even on a risk-adjusted basis.

The impressive performance of the ETF strategies comes with a caveat, however. They exhibit a relatively high portfolio turnover, which may imply elevated trading costs. Roughly 22%–37% of the components of the long-short portfolio are replaced each month, and this number grows for the less diversified (quintile) strategies. Consequently, the breakeven trading costs vary between 1.14% and 1.35%, depending on the strategy.

One way of escaping the costly portfolio reconstructions is through long-only strategies. The long-only portfolios do not require short selling, and the portfolio turnover is typically lower by about a half. From an investor's perspective, they may form a viable alternative for factor construction (Blitz et al., 2020). In our case, the long-only portfolios produce comparable (or even higher) returns than the long-short strategies. They, however, miss the diversification benefit, which is built-in within the construction of the hedge portfolios. Hence, their Sharpe ratios are generally lower than for the long-short strategies.

5.3. Extended holding periods

Another simple way of cutting the transaction fees may be through less frequent portfolio rebalancing (Novy-Marx and Velikov, 2019). Nonetheless, many trading signals tend to be short-term in nature and thus require frequent trading. Does the ΔCLI effect last through extended holding periods? To answer this question, we reproduce our univariate portfolio sorts from Subsection 3.1 by trying four different holding periods: three, six, nine, and 12 months. The results are in Table A19 in the Internet Appendix.

The less frequent portfolio reconstruction adversely affects the ΔCLI strategy performance. However, the impact is not detrimental enough to completely erase the portfolio profits. The mean returns and alphas on the spread strategies remain robust and significant, even when the holding period amounts to nine months. In this case, the average long-short portfolio return is still economically significant, amounting to 0.64% and 0.47% in the equal-weighted and value-weighted frameworks, respectively. Furthermore, they still survive the examination of different factor models, where the COMP alphas amount to 0.45% and 0.35%. When the holding period extends to 12 months, the abnormal returns become insignificant, but only for the value-weighted strategies. The equal-weighted strategies continue to outperform.

To conclude, the ΔCLI effect remains resilient to extending the portfolio holding periods. This observation is especially relevant from a practical angle, as it allows limiting the trading frequency and, effectively, suppression of the transaction costs.

6. Conclusion

In this study, we examine the effect of changes in the leading economic indicators on the cross-section of global stock returns. Using the monthly changes in the OECD CLI, we find that they positively predict future returns. An equal-weighted quintile of markets with high ΔCLI outperforms their low ΔCLI counterparts by 1.43% per month. The effect survives a plethora of robustness checks, including controlling for a battery of other return predictors, extensive subperiod and subsample analysis, application of different factor models, different currency conventions, and alternative explanations.

Our findings have practical implications. The ΔCLI could also be forged into a valuable investment strategy that improves the risk-return profile of a diversified global equity portfolio. The abnormal returns are strong, even when the trading frequency is reduced to nine months, mitigating the adverse impact of trading costs. Finally, the ΔCLI premium may be effectively harvested through ETF investments, which allow for quick reallocation of capital around the world.

The major limitation of our study is the limited sample size. Our conclusions based on 39 countries may be potentially sample-specific. Unfortunately, this constraint cannot be easily overcome, as we have already used all the available data by merging different databases. Perhaps future studies based on fresher and broader datasets can provide additional insight on this issue.

Furthermore, future research should be pursued in at least two directions. First, it would be valuable to extend our studies to other asset classes. For example, do the local indicators affect local corporate or government bond markets? Second, the underlying mechanism of investors' underreaction to the CLI changes may be investigated further. Are its roots behavioral? Or maybe slow-moving capital plays a role here? These questions remain to be resolved.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.finmar.2022.100736.

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