Insights
Sector

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The Importance of Dispersion in Sector Rotation Strategies

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- Dispersion exhibits autoregressive properties that may be useful for tactical sector positioning.
- The autoregressive properties of dispersion appear to be present in various geographies and over multiple timeframes.
- Higher realised dispersion may suggest higher future dispersion over the short run.

Many investors employ sector rotation strategies, whereby investments are reallocated from one sector to another depending on the changing macroeconomic outlook or market conditions. While momentum-based measures remain the most popular way to implement rotation strategies, other measures (such as business cycle indicators and value-based metrics) are also common. With the wide array of ETF vehicles tracking equity sectors in the market, investors have many options for implementing the strategies of their choice. Regardless of the investment strategy investors wish to apply, an important ingredient of success for any rotation strategy is return dispersion.

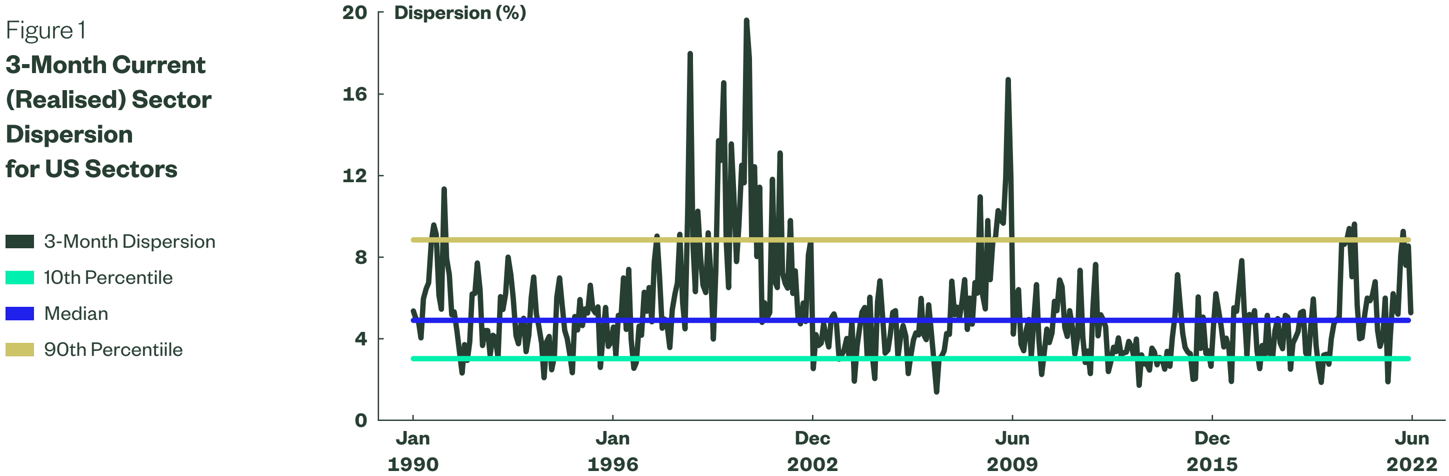
In essence, return dispersion measures the degree to which an index's constituents perform differently from each other. Applied to the context of our analysis, return dispersion measures the variation of performance between sectors. Another way of viewing dispersion is that it measures the degree of uncertainty, and thus risk, associated with holding a particular investment position. The more variable the return of a holding, the riskier it is. In theory, higher levels of dispersion give rise to more plentiful opportunities for investors to successfully execute a rotation strategy.

Notably, most of the dispersion measures that investors focus on are based on historical, overlapping time series. This approach can represent an important drawdown, since such realised dispersion measures may be entirely unrelated to the future. To be sure, the past is hardly ever a reliable forecast of the future; however, the question here is whether current (realised) dispersion numbers are in any way linked to the past, on average, and whether any useful information can be deduced from examining them. To answer this question, we have run a host of statistical tests to assess the time series properties of realised dispersion.

What is current (realised) dispersion telling us?

For much of the year so far, dispersion has stayed at elevated levels, by historical standards, owing to the nervousness in the markets (see Figure 1). Commentators ascribe this to the war in Ukraine as well as the tightening of monetary policies by major central banks. While the most recent dispersion level has fallen somewhat, to around its median, it may spike up again if market uncertainty persists. In the next section, we explore the properties of realised dispersion measures and whether any useful information can be gleaned from them.

Figure 1
3-Month Current (Realised) Sector Dispersion for US Sectors



Source: Bloomberg, State Street Global Advisors, from January 1990 to June 2022. The dispersion calculation above is based on S&P 500 sectors GICS Level 1.

What is dispersion and how is it calculated?

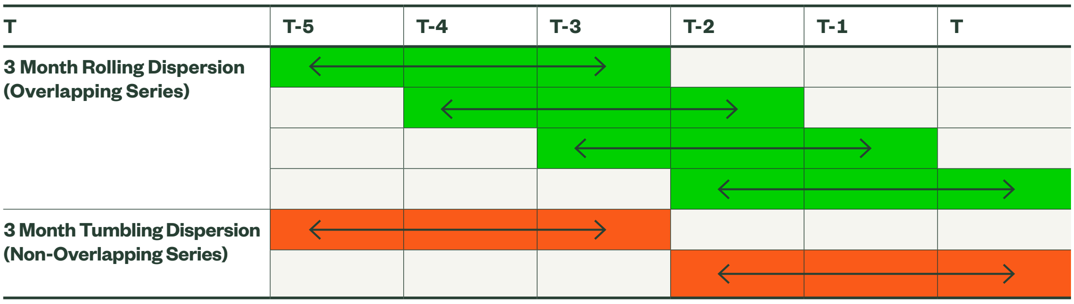
Dispersion over a given time period is calculated as the square root of the cap-weighted sum of the squared benchmark-relative returns of the components (in this case, sectors) over the period in question. (See Equation 1 below.)

$$Dispersion = \sqrt{\sum_{i=1}^{n} w[i] * (r[i] - R)^2} \quad \text{[Eq. 1]}$$

Where W[i] = weight of the i^{th} component in the benchmark r[i] = returns of the i^{th} component and R is the return of the benchmark over a given timeframe.

Most practitioners compute dispersion measures using overlapping time series (see Figure 2). However, for the purposes of our analysis, we analyse both the properties of overlapping and non-overlapping time series. The reason for this is to assess whether the time series properties of dispersion measures would change if we used a different timeframe or rolling window to do the calculation.

Figure 2
Illustration of Overlapping and Non-Overlapping Rolling Windows Used to Compute Dispersion



Source: State Street Global Advisors. For illustrative purposes only.

The Link Between Dispersion and Volatility

In industry parlance, dispersion is referred to as cross-sectional volatility of returns[1] and it is mathematically and structurally similar to volatility.

While dispersion does not explicitly incorporate correlation in its calculation, it is nonetheless highly correlated to option-implied volatility (VIX), as shown by Gorman et al.[2] Therefore, it can be construed as an interplay between volatility and correlation across the components of the benchmark[3] but higher volatility, especially at extreme levels, does not automatically translate into higher dispersion.

Investigating the Properties of Dispersion Measures

We now turn to analysing the properties of dispersion measures. Understanding the properties of current (realised) dispersion is useful to investigate whether current observations have any link with the past (on average) and, if so, the type and strength of that connection. We attempt to describe that connection through fitting the current dispersion time series with common time series models and we assess how good that fit is. These include autoregressive models, moving-average models and mixed autoregressive-moving-average models.

In general, autoregressive models describe a relationship between current data and its past (lagged) values. On the other hand, moving average models represent a dependency between current and past residual error terms and can be viewed as a weighted moving average of past forecast errors. Mixed models include features from both autoregressive and moving-average models.

We have conducted a number of statistical tests to determine if measures of current (realised) dispersion possess any autoregressive and/or moving-average characteristics. To ensure that our analysis is robust, we have applied our analysis to both overlapping and non-overlapping time series, although we recognise that the market conventionally uses overlapping dispersion time series. As a start, we have sought to ascertain whether the time series follows an autoregressive (AR) and/or moving-average (MA) process through visual inspection of their corresponding autocorrelation functions (ACF) and partial autocorrelation functions (PACF).

These plots graphically summarise the strength of a relationship between an observation in a time series and observations at prior time steps. Autocorrelation functions or plots demonstrate the correlation between a given observation and observations with previous time steps, called lags, and this contrasts with partial autocorrelation functions, which summarise the relationship between an observation with observations at prior time lags, while removing the relationships of intervening observations.

Identifying the process of a given time series follows through visual inspection

Once the time series under study is stationary[4] (stabilised), we can then plot the ACF and PACF to try to identify the parameters of the autoregressive-moving-average (ARMA) model. These plots should be considered together to accurately identify the fitted time series process. For a process to be classified as AR, the PACF plot should see a sharp drop after a specified level of statistically significant lags, while the ACF plot should steadily decrease. The opposite holds true for an MA process, which means that the ACF plot should show a material drop after a certain number of statistically significant lags, while the PACF should experience a gradually declining trend. Finally, if both ACF and PACF plots demonstrate a progressively decreasing pattern, then the ARMA process is the most likely.

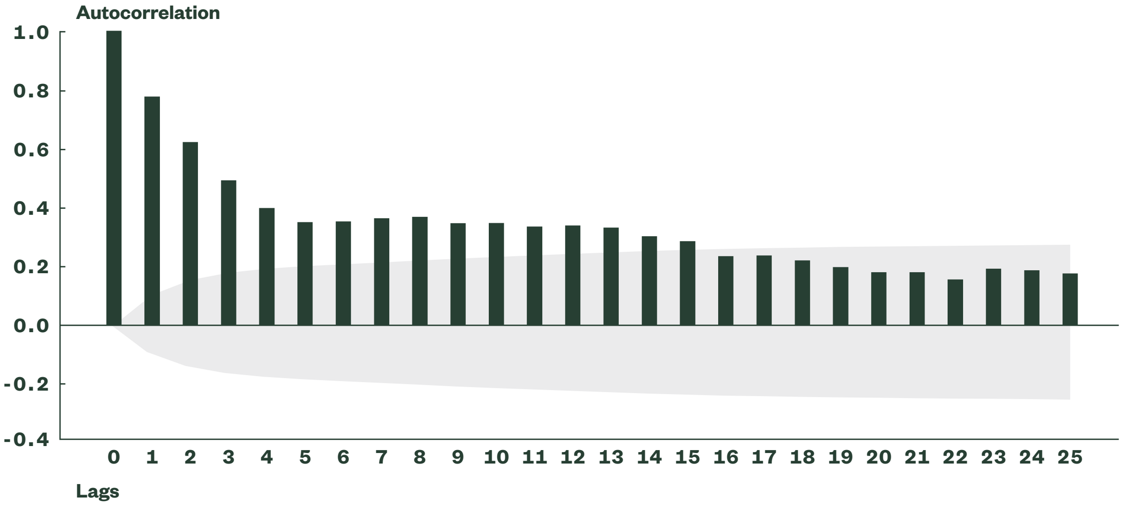
Validating visual results on the basis of formal statistical performance metrics

The next step is to validate our findings, identified visually above, by running formal statistical performance metrics on a variety of possible ARMA models and then select the fitted time series model that has the lowest information criteria (e.g. Akaike Information Ratio (AIC) or Bayesian Information Ratio (BIC)). Both AIC and BIC assess the fit of the time series vis-a-vis its complexity and, in the case of BIC, the number of observations in the fitting process. Generally speaking, AIC and BIC should yield the same conclusion but, where they conflict, BIC is preferred because it offers more stable results and is statistically consistent.

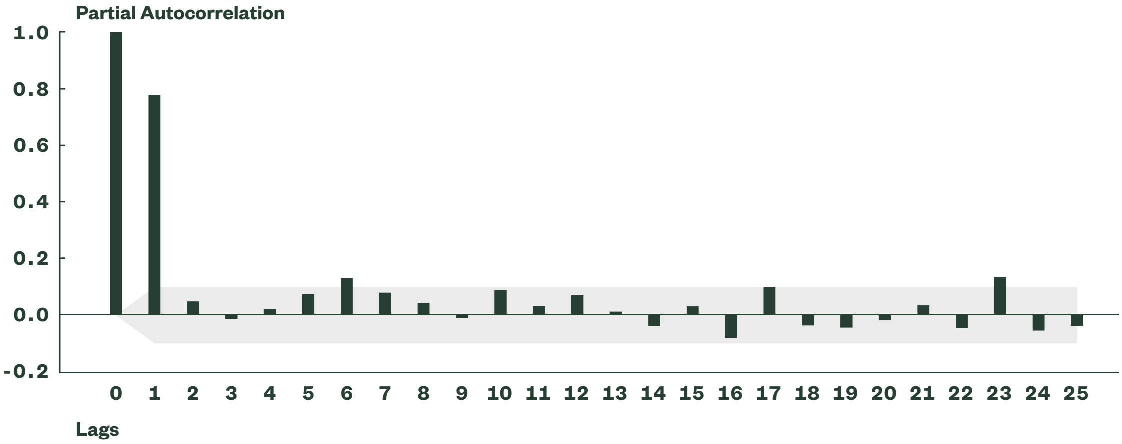
Time series properties of dispersion measures

Figure 3
Autocorrelation and Partial Autocorrelation Function Plots for 6-Month Overlapping Dispersion Time Series Based on US Sectors

a. Autocorrelation Function Plot



b. Partial Autocorrelation Function Plot

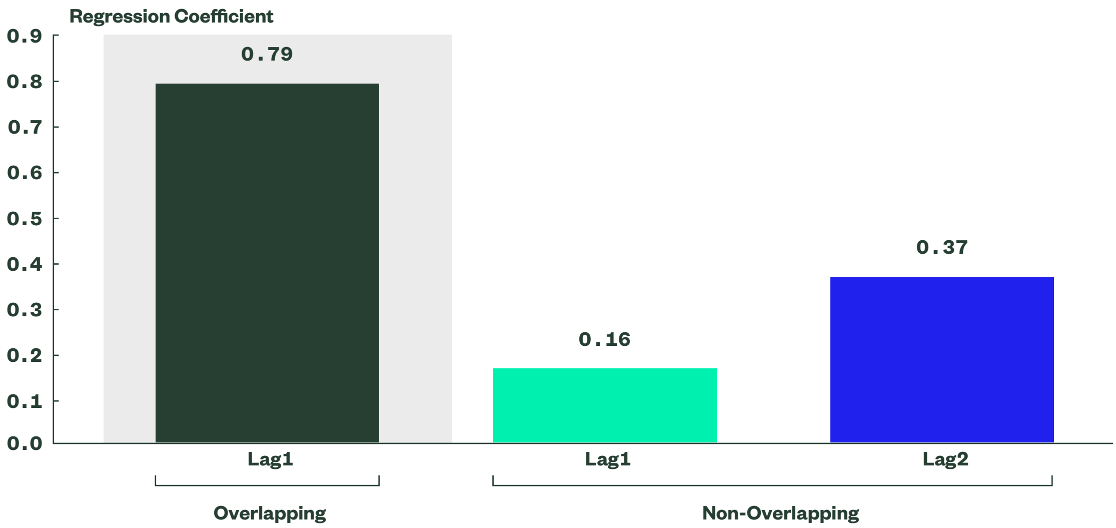


Source: State Street Global Advisors. Data between 1990 and 2022. The grey area highlighted denotes the statistically insignificant area.

The visual inspection of the autocorrelation function plot (ACF) and the partial autocorrelation function plot (PACF) in Figure 3 suggest that six-month dispersion, calculated on overlapping series, follows an autoregressive price process of order 1. This finding is confirmed by selecting the best statistical model based on the lowest information criteria after having iterated through a variety of candidate models.

With regard to the non-overlapping data, dispersion also appears to follow an autoregressive price process of order 2. In other words, both the neighbouring observation and the one prior to that have some influence on the current dispersion level, although the magnitude of the autoregressive behaviour is much weaker in the non-overlapping time series than it is in the overlapping one[5] (see Figure 4). This observation is not surprising, given the construction of the rolling windows in the overlapping and non-overlapping time series. Interestingly, the six-month, non-overlapping time series shows a higher dependence on the second lagged observation than it does on the more recent observation. Outside of the six-month rolling window time series, dispersion for the US generally follows an autoregressive process, except for the three-month rolling window, which follows a moving-average process.

Figure 4
Average Impact of Past Observations on Current Observations Based on 6-Month Dispersion Measures in US Sectors



Source: State Street Global Advisors. Data between 1990 and 2022.

Outside of the US, dispersion also generally displays some kind of autoregressive price processes in the European and world overlapping time series. Although, the results are mixed for non-overlapping time series calculated using dispersion observations of more than three months.

Figure 5
Summary of Analysis on the Time Series Processes Followed by Dispersion Measures

	Overlapping Dispersion Time Series	Non-overlapping Dispersion Time Series
USA		
1 Month	—	Moving-average (ARIMA (0,1,1))
3 Month	Moving-average (ARIMA (0,1,2))	Autoregressive (ARIMA (3,1,0))
6 Month	Autoregressive (AR (1))	Autoregressive (AR (2))
12 Month	Autoregressive (AR (2))	Autoregressive (AR (1))
Europe		
1 Month	—	Autoregressive Moving-average (AR (1), MA(1))
3 Month	Autoregressive Moving-average (AR (1), MA (2))	Autoregressive (AR (2))
6 Month	Autoregressive Moving-average (AR (1), MA (1))	Neither
12 Month	Autoregressive (AR (1))	Neither
World		
1 Month	—	Autoregressive Moving-average (AR (1), MA (1))
3 Month	Autoregressive Moving-average (AR (1), MA (2))	Autoregressive Moving-average (AR (1), MA (1))
6 Month	Autoregressive (AR (1))	Neither
12 Month	Autoregressive (AR (2))	Autoregressive (AR (1))

Source: State Street Global Advisors.

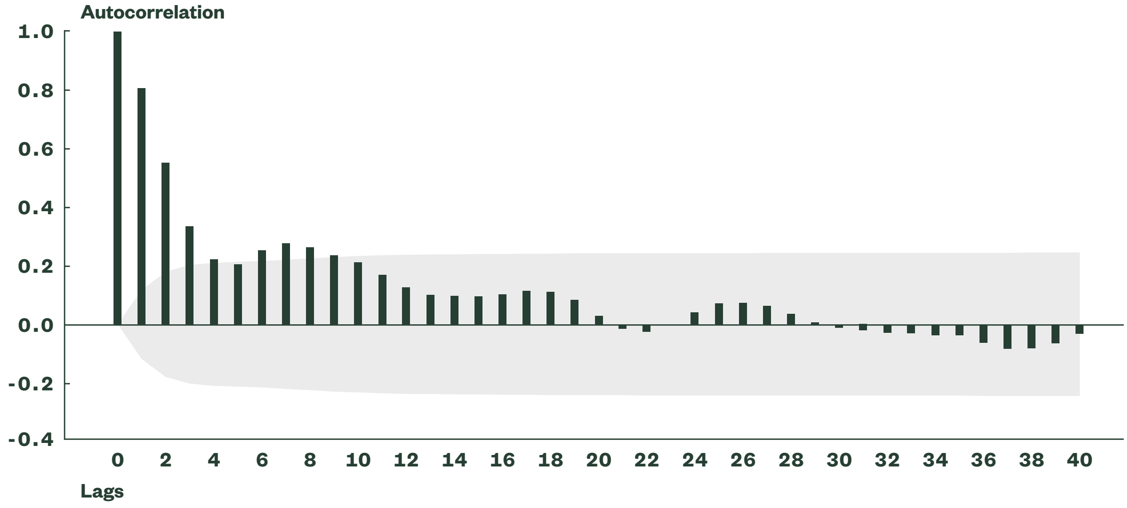
In conclusion, we see that dispersion measured over an overlapping time series, the most common means of calculation, displays a degree of autoregressive properties in the US, Europe and world, and six-month dispersion appears to be the most consistent indicator because it generally follows an autoregressive time series process. Overall, this result suggests that higher realised dispersion may also lead to higher future dispersion, on average.

As shown by Larry R. Gorman et al,[6] periods of market downturns are generally characterised by an increase in return dispersion, volatility and alpha dispersion. That being said, financial markets can sometimes see high dispersion without a market downturn. Regardless of the cause, investors may be able to take advantage of the autoregressive properties of realised dispersion when they position their portfolios for tactical asset allocation, especially because realised (current) dispersion often leads to higher future dispersion over the short run, on average.

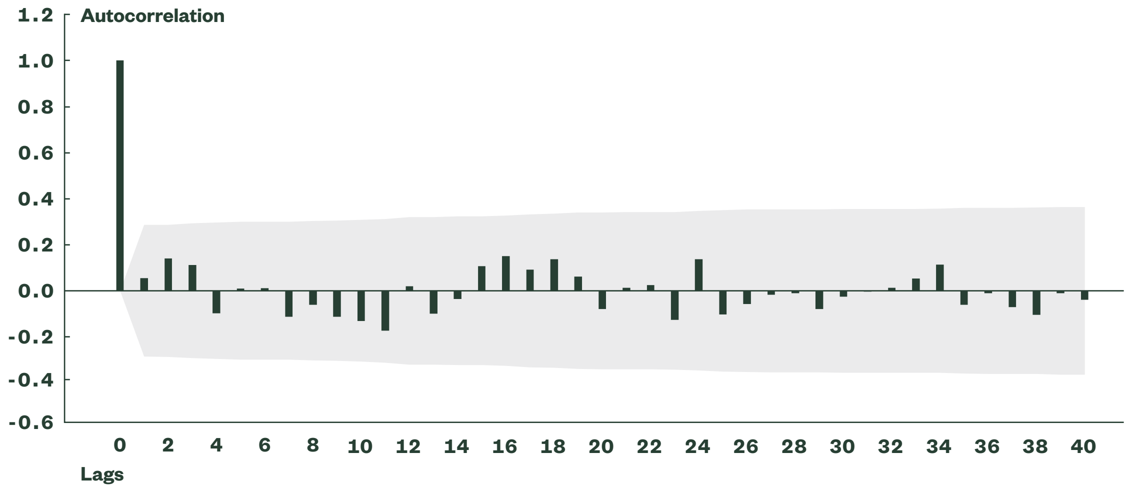
Appendix

Figure 6
Auto Correlation Function (ACF)/ Partial Auto Correlation Function (PACF) Results for Europe Sectors 6-Month Dispersion

a. Autocorrelation Function Plot

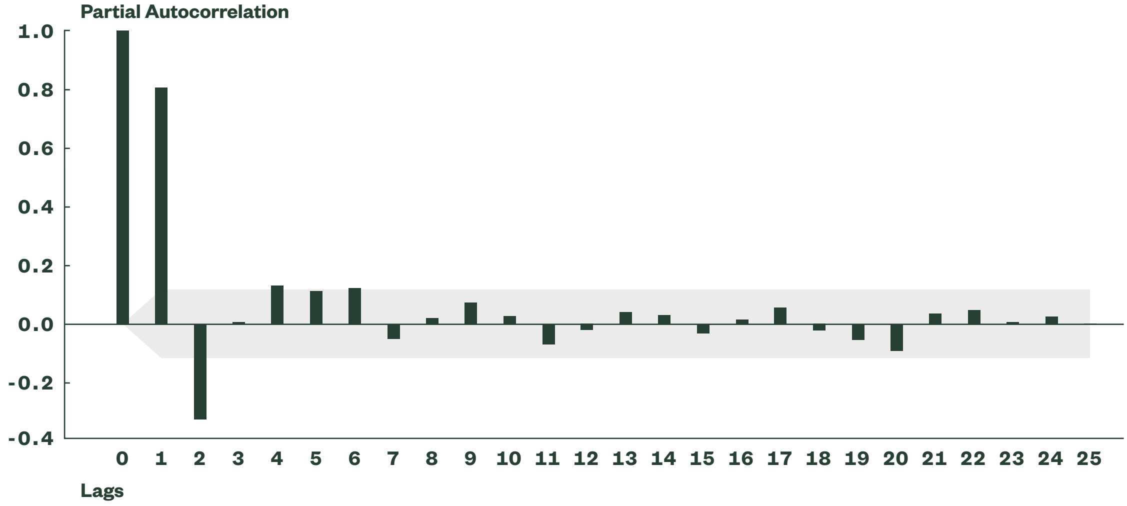


b. Autocorrelation Function Plot (Non-Overlapping)

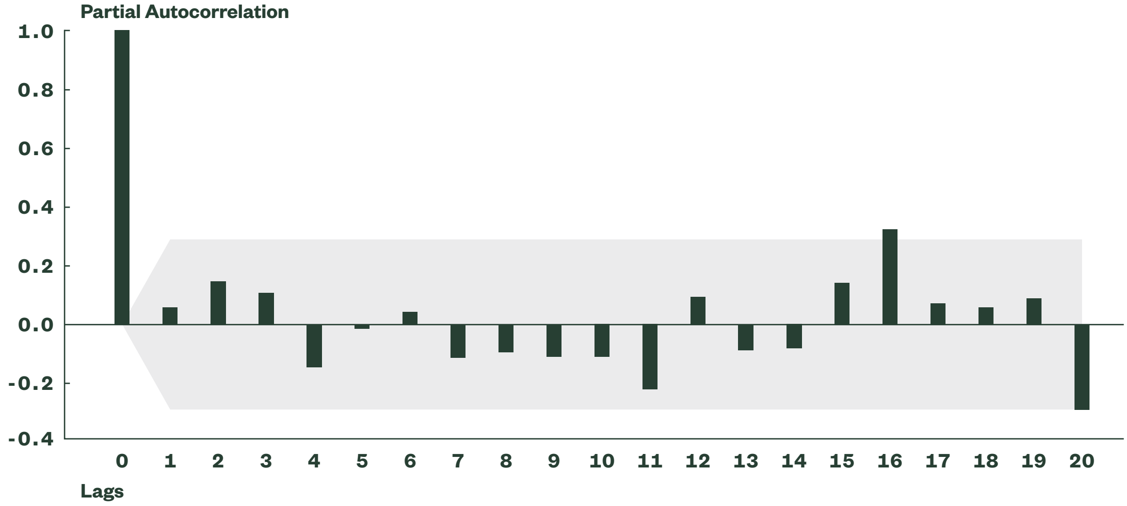


Source: State Street Global Advisors. Data between 1990 and 2022. The grey area highlighted denotes the statistically insignificant area.

c. Partial Autocorrelation Function Plot



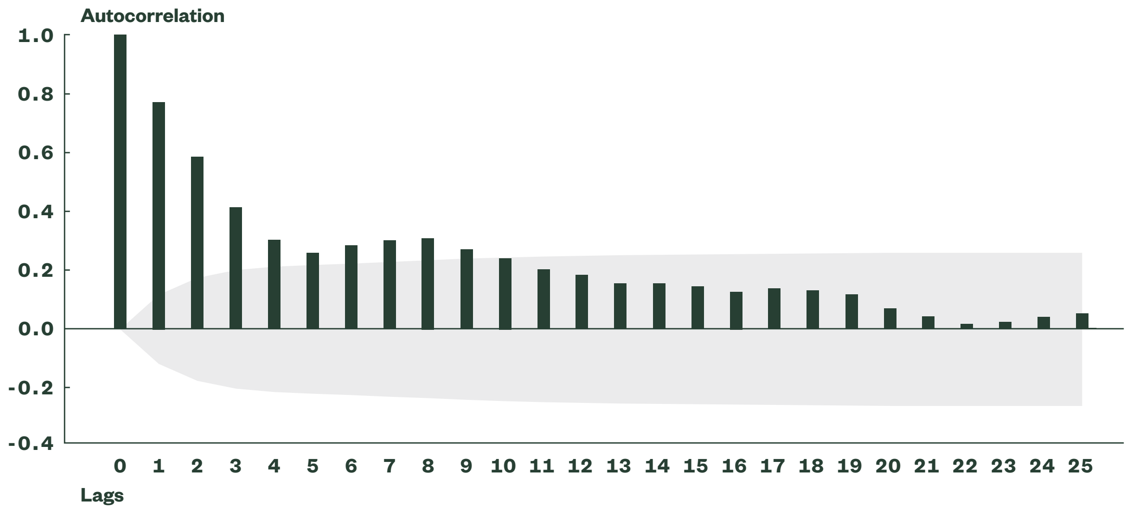
d. Partial Autocorrelation Function Plot (Non-Overlapping)



Source: State Street Global Advisors. Data between 1990 and 2022. The grey area highlighted denotes the statistically insignificant area.

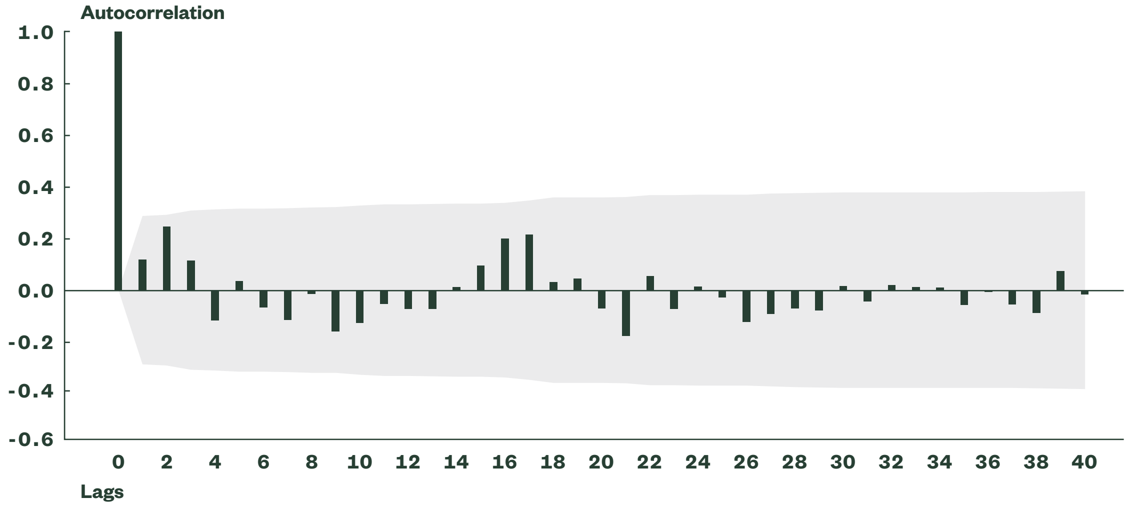
Figure 7
Auto Correlation Function (ACF)/ Partial Auto Correlation Function (PACF) Results for World Sectors 6-Month Dispersion

a. Autocorrelation Function Plot

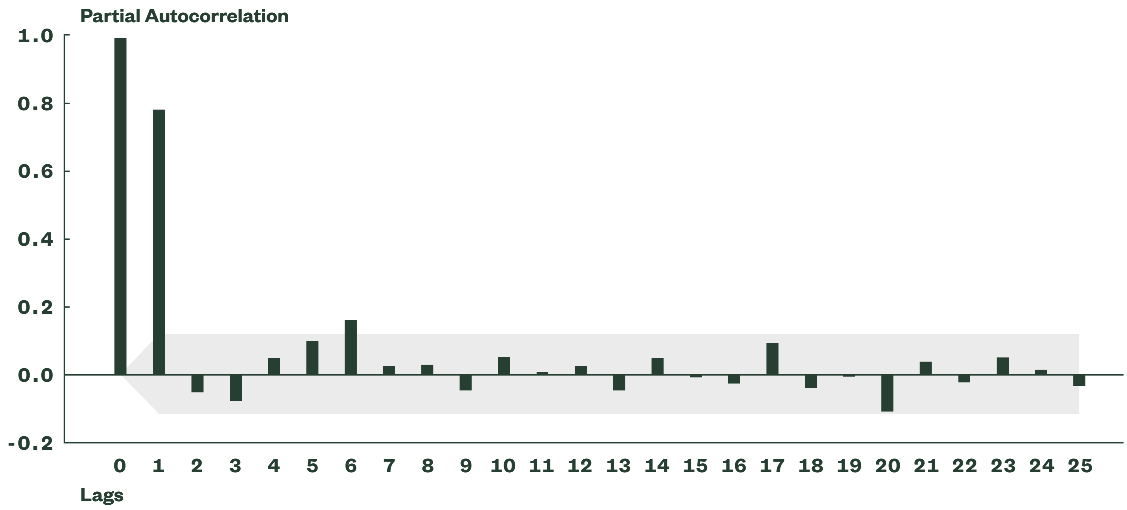


Source: State Street Global Advisors. Data between 1990 and 2022. The grey area highlighted denotes the statistically insignificant area.

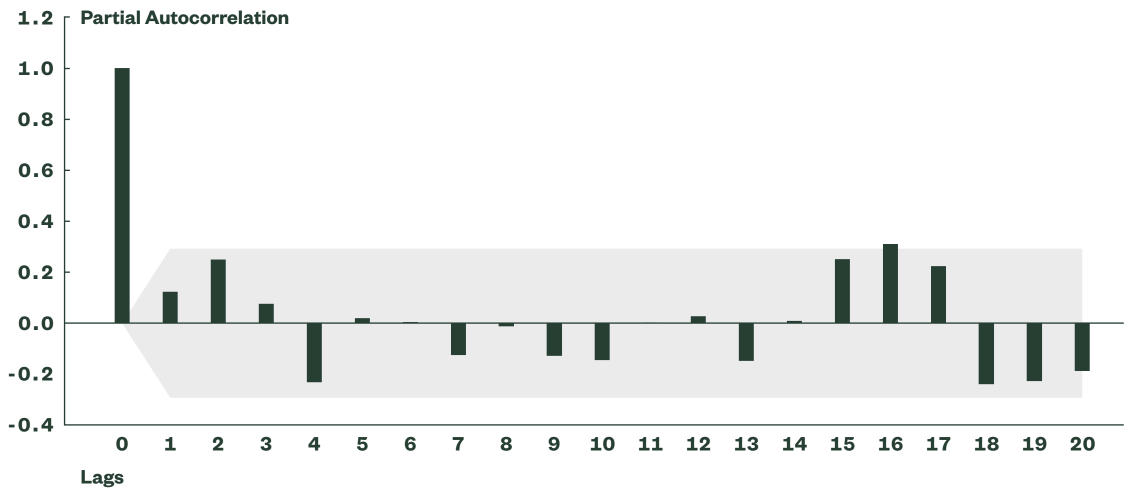
b. Autocorrelation Function Plot (Non-Overlapping)



c. Partial Autocorrelation Function Plot



d. Partial Autocorrelation Function Plot (Non-Overlapping)



Source: State Street Global Advisors. Data between 1990 and 2022. The grey area highlighted denotes the statistically insignificant area.

Endnotes

1 Edwards, Lazarra (2013), *Dispersion: Measuring Market Opportunity*, S&P Dow Jones Indices.

2 The Cross-Sectional Dispersion of Stock Returns, Alpha, and the Information Ratio | The Journal of Investing (pm-research.com).

3 VOLATILITY, DISPERSION & CORRELATION; FRIENDS OR FOES? (factorresearch.com).

4 A stationary time series is one of which the properties do not depend on the time at which it is observed.

5 As evidenced by the coefficients shown in Figure 4.

6 The Cross-Sectional Dispersion of Stock Returns, Alpha, and the Information Ratio | The Journal of Investing (pm-research.com)