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Indexing and stock market serial dependence around the world[☆]

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ABSTRACT

We show a striking change in index return serial dependence across 20 major market indexes covering 15 countries in North America, Europe, and Asia. While many studies find serial dependence to be positive until the 1990s, it switches to negative since the 2000s. This change happens in most stock markets around the world and is both statistically significant and economically meaningful. Further tests reveal that the decline in serial dependence links to the increasing popularity of index products (e.g., futures, exchange-traded funds, and index mutual funds). The link between serial dependence and indexing is not driven by a time trend, holds up in the cross section of stock indexes, is confirmed by tests exploiting Nikkei 225 index weights and Standard & Poor's 500 membership, and in part reflects the arbitrage mechanism between index products and the underlying stocks.

1. Introduction

Since the 1980s, many studies have examined the martingale property of asset prices and shown positive serial dependence in stock index returns. Several explanations for this phenomenon have been posited such as market microstructure noise (stale prices) and slow information diffusion (the partial adjustment model). In this paper, we provide systematic and novel evidence that serial dependence in index returns has turned significantly negative more recently across a broad sample of 20 major market indexes covering 15 countries in North America, Europe, and the Asia-Pacific. Negative serial dependence implies larger and more frequent index return reversals that cannot be directly accounted for by traditional explanations.

Our key result is illustrated in Fig. 1, which plots several measures for serial dependence in stock market returns averaged over a ten-year rolling window. While first-order autocorrelation [AR(1)] coefficients from daily returns have traditionally been positive, fluctuating around 0.05 from 1951, they have been steadily declining ever since the 1980s and switched sign during the 2000s. They have remained negative ever since.

This change is not limited to first-order daily autocorrelations. For instance, AR(1) coefficients in weekly returns evolved similarly and switched sign even before 2000. Because we do not know a priori which lag structure comprehensively measures serial dependence, we examine a novel measure for serial dependence, multi-period autocorrelation [MAC(q)], that incorporates serial dependence at multiple (that is, q) lags. For instance, MAC(5) incorporates daily serial dependence at lags one through four.

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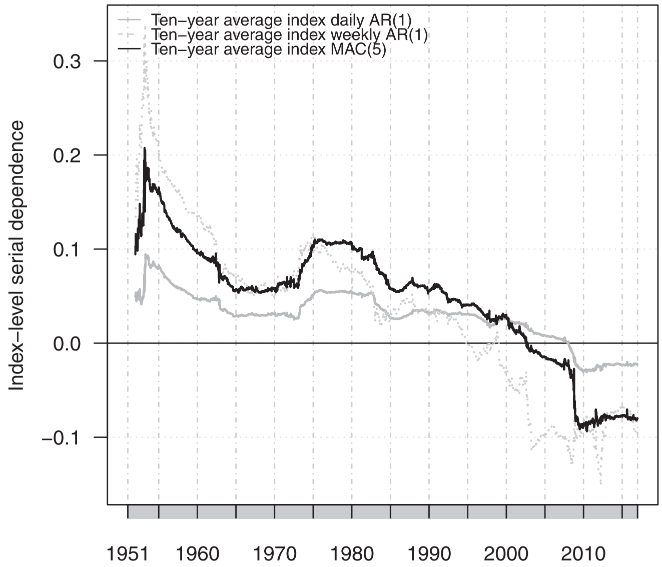

Fig. 1. Evolution of index-level serial dependence. This figure plots the evolution of serial dependence in index returns from January 1, 1951 to December 31, 2016. Serial dependence is measured by first-order autocorrelation from index returns at the daily frequency ["daily AR(1)"], first-order autocorrelation from index returns at the weekly frequency sampled at Wednesdays ["weekly AR(1)"], and multi-period autocorrelation in index returns with q equal to five ["index MAC(5)"]. All three serial dependence measures are equal-weighted across each of the indexes in the sample. Plotted is the moving average of these measures using a ten-year window (for the first ten years, the window expands from one year to ten years).

MAC(q) can be directly mapped to the traditional variance ratio test that places linearly declining weights on higher-order autocorrelations. Such a declining weighting scheme provides an asymptotically powerful test for return serial correlation (Richardson and Smith, 1994). Fig. 1 demonstrates that incorporating multiple lags by using MAC(5) also reveals a dramatic change in serial dependence over time.

The new MAC(q) measure is estimated from a trading strategy, allowing us to demonstrate that negative serial dependence in index returns is economically important. For instance, a strategy that trades against MAC(5) using all indexes in our sample [or the Standard & Poor's (S&P) 500 index alone] would result in an annual Sharpe ratio of 0.63 (0.67) after March 2, 1999 (the most recent date used in previous index autocorrelation studies). In addition, serial dependence in the futures and exchange-traded funds (ETFs) covering our equity indexes is negative ever since their inception. Similar Sharpe ratios are observed for futures and ETFs.

Our results reveal that the decrease of index-level serial dependence into negative territory coincides with indexing, i.e., the rising popularity of equity index products such as equity index futures, ETFs, and index mutual funds. Panel A of Fig. 2 plots the evolution of equity indexing for the S&P 500 based on index futures (black line), index ETFs (solid gray line), and index mutual funds (dashed gray line). The extent of indexing is measured by the total open interest for equity index futures, total market capitalization for ETFs, or total assets under management for index mutual funds, all scaled by the total capitalization of the S&P 500 constituents. Over our sample period, the total value of these index products has increased to about 7% of the total S&P 500 market capitalization.[1] To see this trend on a global level, we plot the evolution of global equity indexing based on index futures and ETFs in Panel B. Equity index products worldwide represented less than 0.5% of the underlying indexes before the 1990s, but the fraction rises exponentially to more than 3% in the 2010s.

From Figs. 1 and 2, indexing and negative index serial dependence clearly are correlated. We show that this correlation is highly significant and not simply driven by a common time trend. While most of the existing studies focus on one market or one index product, we examine 20 major market indexes (covering North America, Europe, and Asia-Pacific) and multiple index products (futures and ETFs). The broad coverage and considerable cross-market variation in futures introduction dates, ETF introduction dates, and the importance of indexing (relative to the index) provide independent evidence for a link between indexing and negative serial dependence in the underlying index, in several ways.

First, for each index, we endogenously determine when its serial dependence changed dramatically using a purely statistical, data-driven approach. In the cross section of indexes, we find a highly significantly positive relation between the break date in index serial dependence and the start of indexing measured by the introduction date of index futures. In the time series, cumulative serial dependence follows an inverse U-shape that peaks less than five

[1] We count only listed index products that directly track the S&P 500 in this number, and we ignore enhanced active index funds, smart beta funds, index products on broader indexes (such as the MSCI country indices), and index products on subindexes (such as the S&P 500 Value Index). Thus, this percentage errs on the conservative side.

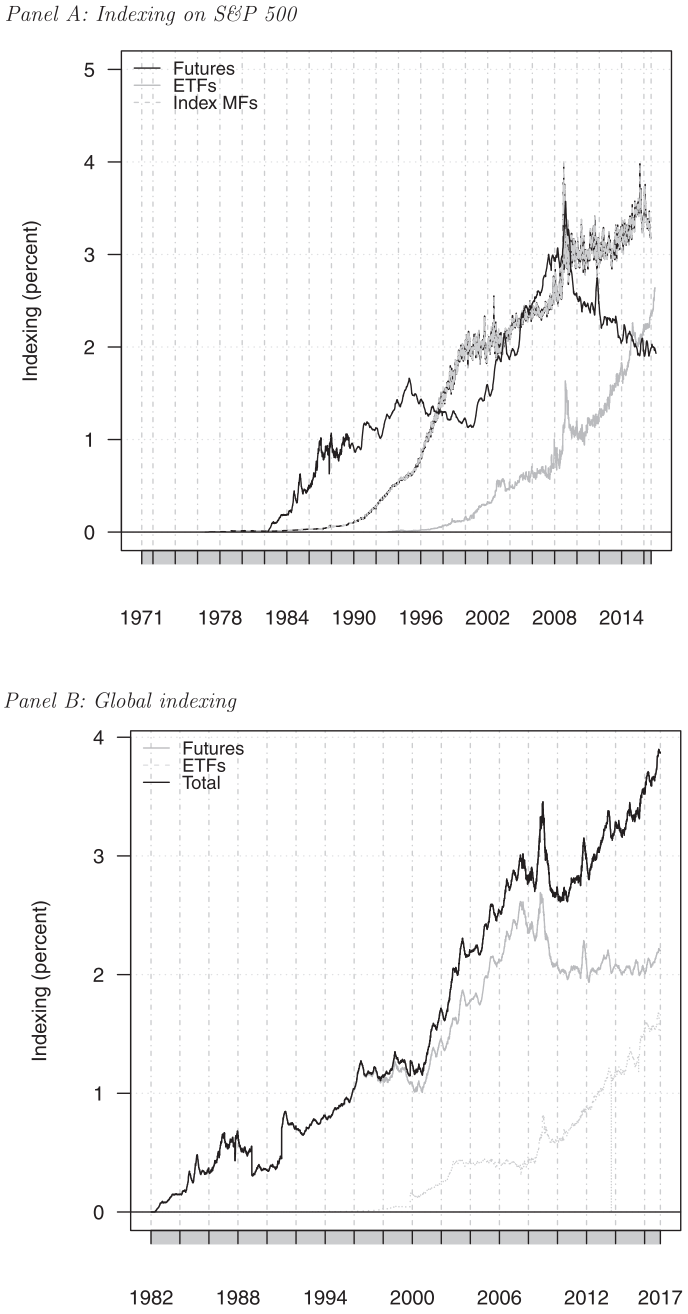

Fig. 2. Evolution of indexing. This figure plots the evolution of indexing in the Standard & Poor's (S&P) 500 (Panel A) and across the world (Panel B). Indexing is measured for futures ("Futures") as total open interest (in monetary units) divided by total index market capitalization, and for exchange-traded funds (ETFs) as total ETF market capitalization divided by total index market capitalization. Panel A plots these measures for the S&P 500, together with total market capitalization for S&P 500–based equity index mutual funds ("Index MFs"). Panel B plots these measures aggregated across the stock market indexes in our sample excluding the NASDAQ, NYSE, and S&P 400 because open interest data from either Bloomberg or Datastream are available only four to ten years after the futures introduction. This global indexing measure is weighted with the index market capitalization across each of the indexes in the sample. The sum of the futures and ETF measures is total indexing ("Total").

years after the start of indexing. Hence, introducing indexing products seems to change the behavior of the underlying stock market across indexes and over time.

Second, we present cross-sectional and time series evidence that, on average, higher levels of indexing are associated with more negative serial dependence. Across indexes and over time, index serial dependence is significantly lower for indexes with a larger fraction of market capitalization being indexed. The cross-sectional relation is verified using Fama-MacBeth regressions. In the time series, the significantly negative relation survives when we remove the time trend, regress quarterly changes in MAC(5) on quarterly changes in indexing, or add index fixed effects. Thus, increases in indexing are associated with decreases in serial dependence that go beyond sharing a common time trend, and the link cannot be explained by differences between stock markets.

The link between indexing and index-level negative serial dependence could be spurious. For instance, higher demand for trading the market portfolio results in correlated price pressure on all stocks, which could also make index serial dependence turn negative. In other words, index serial dependence could have changed due to market-wide developments, regardless of whether index products have been introduced or not. One could even argue that the futures introduction date is endogenous and futures trading is introduced with the purpose of catering to market-level order flow. In this paper, we identify the impact of indexing on the index by comparing otherwise similar stocks with very different indexing exposure that arise purely from the specific design of the index. We do this in two ways.

First, we exploit the relative weighting differences of Japanese stocks between the Nikkei 225 index and the Tokyo Stock Price Index (TOPIX). Because the Nikkei 225 is price weighted and the TOPIX is value weighted, some small stocks are overweighted in the Nikkei 225 when compared with their market capitalization-based weight in the TOPIX. Greenwood (2008) finds that overweighted stocks receive proportionally more price pressure and uses overweighting as an instrument for non-fundamental index demand that is uncorrelated with information that gets reflected into prices. We employ the Greenwood (2008) approach and find that overweighted Nikkei 225 stocks (relative to their underweighted counterparts) experience a larger decrease in serial dependence as the Nikkei 225 futures is introduced, and the wedge between the two groups widens with the relative extent of indexing between the Nikkei 225 and TOPIX.

In an additional test, we construct an index based on the 250 smallest S&P 500 stocks and compare it with a matching portfolio based on the 250 largest non–S&P 500 stocks. The non–S&P stocks are larger, better traded, and suffer less from microstructure noise and slow information diffusion, yet they are unaffected by S&P 500 index demand. We find that before any indexing, serial dependence is less positive in large non-S&P stocks, as we expect for larger and better traded stocks. However, as indexing rises, serial dependence in the small and lesser traded S&P stocks decreases more than serial dependence in the (larger and better traded) non-S&P stocks and turns negative. This evidence suggests that index membership by itself leads to an additional decrease in serial dependence.

Negative index serial dependence suggests the existence of non-fundamental shocks such as price pressure at the index level. The fact that serial dependence is negative for both the index product and the index suggests that arbitrage is taking place between the two markets. As discussed in Ben-David et al. (2018), such arbitrage can propagate price pressure from the index product to the underlying index.[2] It could also operate in the other direction by propagating price pressure from the index to index product. We confirm the important role of index arbitrage by demonstrating that index serial dependence tracks index product serial dependence very closely, and more so when indexing is higher. In other words, as indexing products become more popular, index arbitrage exposes the underlying index more to price pressure, potentially contributing to its negative serial dependence.

Our study relates to a long literature on market-level serial dependence in stock returns, including (Hawawini, 1980; Conrad and Kaul, 1988; 1989; 1998; Lo and MacKinlay, 1988; 1990a). This literature offers several explanations for positive serial dependence including time-variation in expected returns (Conrad and Kaul, 1988; Conrad et al., 1991), market microstructure biases such as stale prices and infrequent trading (Fisher, 1966; Scholes and Williams, 1977; Atchison et al., 1987; Lo and MacKinlay, 1990a; Boudoukh et al., 1994) and lead-lag effects as some stocks respond more sluggishly to economy-wide information than others (Brennan et al., 1993; Badrinath et al., 1995; Chordia and Swaminathan, 2000; McQueen et al., 1996). We determine that serial dependence has since turned negative as index products became popular, a finding that cannot be explained by these theories but could be explained by the index-level price pressure arising from the index arbitrage that index products enable. Empirically, our story is in line with Duffie (2010), who presents examples from various markets of negative serial dependence due to supply and demand shocks. Furthermore, a related literature exists on short-term return reversal phenomena at the stock level (Avramov et al., 2006; Lehmann, 1990; Hou, 2007; Nagel, 2012; Jylhä et al., 2014). Our study appears related to studies documenting that individual stock returns are negatively autocorrelated, but focuses on serial dependence at the index level. The key distinction is that stock-specific shocks can drive stock-level short-term return reversal, but contribute only marginally to portfolio-level serial dependence for any well diversified stock index or portfolio.

Our paper also relates to existing work that links indexing to side effects such as the amplification of fundamental shocks (Hong et al., 2012), non-fundamental price changes (Chen et al., 2004), excessive co-movement (Barberis et al., 2005; Greenwood, 2005; 2008; Da and Shive, 2017), a deterioration of the firm's information environment (Israeli et al., 2014), increased non-fundamental volatility in individual stocks (Ben-David et al., 2018), and reduced welfare of retail investors (Bond and García, 2017). Our results indicate a balanced perspective on the effects of index products. On the one hand, they point to positive features of index products, which are generally easier to trade than the underlying stocks. Also, because futures traders have higher incentives to collect market-wide information (Chan, 1990; 1992), indexing allows for faster

[2] This mechanism is underpinned by theory in Leippold et al. (2015). Bhattacharya and O'Hara (2015) demonstrate theoretically that similar shock propagation can occur due to imperfect learning about informed trades in the index product. For further intuition on the arbitrage mechanism, see Ben-David et al. (2018) Fig. 1, and Greenwood (2005).

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incorporation of common information and, therefore, reduces the positive index serial dependence. On the other hand, significantly negative index serial dependence can be explained only by short-term deviations from fundamental value and subsequent reversal, and it reflects the existence of non-fundamental shocks even at the index level. This result is consistent with the view in Wurgler (2011) that too much indexing can have unintended consequences by affecting the general properties of markets and even triggering downward price spirals in an extreme case (e.g., Tosini, 1988).

This paper proceeds by describing the data in Section 2. In Section 3, we use several measures for serial dependence to show that index-level serial dependence has changed over time from positive to negative. In Section 4, we show that this decrease in serial dependence is associated with increased popularity of index products. In Section 5, we argue that negative serial dependence arises because of indexing, and that index arbitrage spreads negative serial dependence between index products and the underlying index. We conclude in Section 6.

2. Data

To examine serial dependence in index returns and the effect of indexing, we collect data for the world's largest, best traded, and most important stock indexes in developed markets around the world, as well as for their corresponding futures and ETFs. To avoid double counting, we exclude indexes such as the Dow Jones Industrial Average whose constituents are completely subsumed by the constituents of the S&P 500. We also verify, in the Online Appendix, that our results are similar when we consider only one index per country. The sample period runs from each equity index's start date (or January 1, 1951, whichever comes later) up to December 31, 2016 or when all futures on the index have stopped trading (this happens for the NYSE futures on September 15, 2011). We thus can examine a cross section of major indexes that vary considerably in index, futures, and ETF characteristics.

We use Bloomberg data to obtain market information on equity indexes (index prices, total returns, local market capitalizations, daily traded volume, dividend yields, and local risk free rates), equity futures (futures prices, volume, open interest, and contract size to aggregate different futures series on one index), and ETFs (ETF prices, market capitalization, volume, and weighting factors for leveraged or inverse ETFs, or both). Because an ETF for a given index typically trades at many different stock markets, we obtain a list of existing equity index ETFs across the world based on ETFs on offer from two major broker-dealers. Because we focus on index products that closely track the underlying index, we do not include ETFs on a subset of index constituents, active ETFs, or enhanced ETFs (e.g., smart beta, alternative, factor-based, etc.). Finally, for the analysis in Section 5, we obtain information on Nikkei 225 and S&P 500 index membership from Compustat Global's Index Constituents File and the Center for Research in Security Prices (CRSP) Daily S&P 500 Constituents file, respectively. Appendix A describes the indexes, as well as the construction of data and variables, in detail.

Below, Table 1 reports on the 20 major market indexes in our sample covering countries across North America, Europe, and the Asia-Pacific region. Column 2 shows that, in our sample, index series start as early as 1951 and as late as 1993. Means and standard deviations of index returns in Columns 3 and 4 show no major outliers.

3. Serial dependence in index returns

In this Section, we show that index-level serial dependence has changed from positive to negative in recent years. Section 3.1 does so using AR(1) coefficients to proxy for serial dependence, in line with the existing literature. In Section 3.2, we suggest multiperiod autocorrelation (with linearly or exponentially declining weights) as a more comprehensive way to measure serial dependence.

3.1. International evidence on serial dependence: past and present

Short-term serial dependence in daily returns on index portfolios is a classic feature of stock markets that has always been positive (see, among others, Fama, 1965; Fisher, 1966; Schwartz and Whitcomb, 1977; Scholes and Williams, 1977; Hawawini, 1980; Atchison et al., 1987; Lo and MacKinlay, 1988; Lo and MacKinlay, 1990b). To our knowledge, we are the first to show systematically that serial dependence around the world has recently turned negative. However, decreasing serial dependence has previously appeared in bits and pieces throughout the literature. For instance, index-level serial dependence seems to decrease over time in Lo and MacKinlay (1988), Boudoukh et al. (1994) (1994, Table 2), and Hou (2007, Table 2). Ahn et al. (2002) (Table 2) find that serial dependence is close to zero more recently for a range of indexes with futures contracts and liquid, actively traded stocks. Chordia et al. (2008) (2008, Table 7.B) find that daily first-order autocorrelations of the portfolio of small NYSE stocks have decreased from significantly positive during the 1/8th tick size regime (from 1993 to mid-1997) to statistically indistinguishable from zero during the 0.01 tick size regime (from mid-2001 until the end of their sample period). Finally, Chordia et al. (2005) (Table 1) find that autocorrelations are smaller in more recent subperiods.

To provide systematic evidence that serial dependence has decreased over time, a natural point of departure is extending the sample period of earlier work. We split the sample into two subperiods, with the first period (before) running until the end of the most recent paper examining autocorrelations in both domestic and international stock markets, Ahn et al. (2002). The second period (after) begins on March 3, 1999, one day after their sample period ends. For each index, Ahn et al. (2002) collect data only from when the corresponding futures contract becomes available. We collect data for each index that goes back as far as possible to analyze serial dependence both before and after futures were introduced. While the results in Table 1 are therefore not directly comparable to Ahn et al. (2002), we verify that AR(1) coefficients are very similar when estimated over the same sample period.

Table 1
Recent changes in serial dependence.
This table describes all stock markets in our sample in terms of index series start dates ("Series start"), the annualized sample average ("Average") and the annualized standard deviation ("Standard deviation") of daily index returns, and serial dependence. The columns labeled "Daily AR(1)" and "Weekly AR(1)" present autocorrelation coefficients for returns at the daily or weekly frequency, respectively. We report statistics before and after March 3, 1999 ("Before," "After") and test for the difference in the columns labeled "*t*(diff.)." The row labeled "Panel of indexes" reports results from a pooled regression across all of the individual indexes in an equal-weighted panel. The row labeled "Panel of indexes (one-day lag)" does so after incorporating a one-day implementation lag [i.e., daily AR(1) becomes AR(2)]. Reported *t*-values (in parentheses) are based on standard errors that are Newey-West corrected for individual indexes and double-clustered across indexes and time when all indexes are pooled together. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

					Daily AR(1)			Weekly AR(1)		
Index	Country	Series Start	Average	Standard deviation	Before	After	*t*(diff.)	Before	After	*t*(diff.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
S&P 500	US	1/1/51	0.082	0.154	0.103***	−0.076***	−6.64***	0.037	−0.077	-2.07**
					(7.45)	(−3.29)		(1.28)	(−1.64)	
FTSE 100	UK	2/1/78	0.048	0.176	0.053***	−0.037**	−3.43***	0.034	−0.102**	-1.70*
					(2.86)	(−1.99)		(0.54)	(−2.07)	
DJESI 50	Eurozone	1/1/87	0.050	0.214	0.041	−0.029	−2.26**	−0.013	−0.155**	-1.40
					(1.62)	(−1.63)		(−0.14)	(−3.25)	
TOPIX	Japan	1/1/51	0.083	0.170	0.121***	0.016	−4.41***	0.068***	−0.058	-2.86***
					(8.10)	(0.89)		(2.69)	(−1.60)	
ASX 200	Australia	6/1/92	0.065	0.153	0.070**	−0.025	−2.51**	−0.067	−0.038	0.37
					(2.10)	(−1.41)		(−1.12)	(−0.78)	
TSE 60	Canada	2/1/82	0.051	0.166	0.167***	−0.038*	−5.42***	0.046	−0.028	-1.06
					(5.32)	(−1.81)		(0.91)	(−0.58)	
CAC 40	France	7/10/87	0.056	0.223	0.043*	−0.030*	−2.45**	−0.047	−0.166***	-1.34
					(1.80)	(−1.68)		(−0.64)	(−3.29)	
DAX	Germany	10/2/59	0.049	0.196	0.066***	−0.016	−3.49***	0.008	−0.102**	-1.96**
					(4.28)	(−0.90)		(0.25)	(−2.24)	
IBEX 35	Spain	1/6/87	0.077	0.224	0.153***	0.004	−4.64***	0.019	−0.097***	-1.38
					(5.79)	(0.19)		(0.25)	(−2.63)	
MIB	Italy	1/1/93	0.067	0.247	0.043	−0.023	−1.76*	−0.036	−0.083**	-0.67
					(1.28)	(−1.37)		(−0.64)	(−1.97)	
AEX	Netherlands	1/4/83	0.088	0.212	0.014	−0.008	−0.62	0.030	−0.115*	-1.29
					(0.50)	(−0.36)		(0.31)	(−1.90)	
OMX Stockholm	Sweden	12/19/86	0.118	0.232	0.117***	−0.029	−4.54***	−0.015	−0.135***	-1.51
					(4.47)	(−1.56)		(−0.23)	(−2.85)	
SMI	Switzerland	7/4/88	0.073	0.184	0.047	0.027	−0.55	0.050	−0.141***	−2.64***
					(1.52)	(1.36)		(0.98)	(−2.76)	
Nikkei 225	Japan	1/2/51	0.087	0.192	0.042***	−0.031	-3.03***	0.047**	−0.018	−1.64*
					(2.79)	(−1.65)		(1.91)	(−0.58)	
HSI	Hong Kong	11/24/69	0.171	0.286	0.059***	−0.012	−2.31**	0.142***	−0.012	−2.65***
					(2.80)	(−0.54)		(3.03)	(−0.35)	
Nasdaq 100	US	2/5/85	0.115	0.265	0.071**	−0.065***	−3.45***	−0.001	−0.074	−1.06
					(2.23)	(−2.79)		(−0.02)	(−1.63)	
NYSE	US	1/3/66	0.036	0.160	0.145***	−0.059**	−6.96***	0.039	−0.079	−1.86*
					(8.39)	(−2.50)		(1.06)	(−1.52)	
Russell 2000	US	1/1/79	0.066	0.191	0.273***	−0.062**	−6.33***	0.192***	−0.065	−3.25***
					(5.83)	(−2.52)		(2.92)	(-1.48)	
S&P 400	US	1/1/91	0.110	0.194	0.147***	−0.033	−5.01***	−0.001	−0.064	−0.78
					(5.38)	(−1.41)		(−0.01)	(−1.25)	
KOSPI 200	South Korea	9/10/87	0.034	0.277	0.057**	0.011	−1.47	−0.042	−0.024	0.25
					(2.32)	(0.58)		(−0.68)	(−0.59)	
Panel of indexes					0.094***	−0.026*	−5.30***	0.042	−0.082**	−2.86***
					(5.58)	(−1.94)		(1.54)	(−2.32)	
Panel of indexes (one-day lag)					−0.009	−0.029*	−0.88	0.065***	−0.021	−2.43**
					(−0.62)	(−1.78)		(3.06)	(−0.74)	

Table 2
Two multi-period autocorrelation measures.
This table presents the two serial dependence measures from Section 3 for all stock markets in our sample. Columns labeled "MAC(5)$_{index}$" present multi-period autocorrelation coefficients with linearly declining weights, as in Eq. (2). Columns labeled "EMAC(5)$_{index}$" present multi-period autocorrelation coefficients with exponentially declining weights, as in Eq. (3). Both serial dependence measures are calculated using daily index returns. We report statistics before and after March 3, 1999 ("Before," "After") and test for the difference in the columns labeled "t(diff.)." The row labeled "Panel of indexes" reports results from a pooled regression across all of the individual indexes in an equal-weighted panel. The row labeled "Panel of indexes (one-day lag)" does so after incorporating a one-day implementation lag [i.e., $\text{MAC}(5) = r_t(4r_{t-2} + 3r_{t-3} + 2r_{t-4} + 1r_{t-5})/5\sigma^2$ and $\text{EMAC}(5)_t = r_t \cdot f(\lambda_5, r_{t-\tau})/\sigma^2, \tau = 2, \ldots, \infty,$]. Reported t-values (in parentheses) are based on standard errors that are Newey-West corrected for individual indexes and double-clustered across indexes and time when all indexes are pooled together. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Index	MAC(5)$_{index}$			EMAC(5)$_{index}$		
	Before	After	t(diff.)	Before	After	t(diff.)
	(1)	(2)	(3)	(4)	(5)	(6)
S&P 500	0.050***	−0.141***	−4.30***	0.014***	−0.048***	−4.46***
	(3.11)	(−3.41)		(3.17)	(−3.64)	
FTSE 100	0.031**	−0.091***	−4.13***	0.009*	−0.031***	−4.25***
	(2.18)	(−3.52)		(1.68)	(−4.02)	
DJESI 50	0.003	−0.077***	−2.76***	0.003	−0.029***	−3.25***
	(0.22)	(−3.12)		(0.51)	(−3.71)	
TOPIX	0.082***	−0.025	−2.54***	0.026***	−0.014	−4.90***
	(5.99)	(−0.63)		(5.82)	(−1.09)	
ASX 200	0.029	−0.044*	−2.09**	0.003	−0.016**	−1.72
	(1.15)	(−1.82)		(0.37)	(−2.13)	
TSE 60	0.100***	−0.075**	−4.93***	0.029***	−0.029***	−4.64***
	(5.29)	(−2.49)		(4.51)	(−2.72)	
CAC 40	0.020	−0.074***	−3.27***	0.007	−0.028***	−3.53***
	(1.13)	(−3.26)		(0.97)	(−3.98)	
DAX	0.012	−0.042	−1.65	0.005	−0.018*	−2.02**
	(0.99)	(−1.38)		(1.10)	(−1.73)	
IBEX 35	0.099***	−0.044*	−3.62***	0.031***	−0.018***	−3.66***
	(3.10)	(−1.91)		(2.75)	(−2.50)	
MIB	0.043	−0.031	−1.98**	0.010	−0.012*	−1.68*
	(1.37)	(−1.54)		(0.90)	(−1.68)	
AEX	−0.005	−0.033	−0.94	0.003	−0.014*	−1.64*
	(−0.28)	(−1.32)		(0.43)	(−1.74)	
OMX Stockholm	0.079***	−0.066***	−4.48***	0.025***	−0.024***	−4.46***
	(3.07)	(−3.36)		(2.73)	(−3.93)	
SMI	0.027	−0.016	−1.11	0.010	−0.014	−1.89*
	(0.95)	(−0.60)		(1.05)	(−1.65)	
Nikkei 225	0.030**	−0.077**	−2.67***	0.010**	−0.024*	−2.63***
	(2.28)	(−2.03)		(2.43)	(−1.95)	
HSI	0.086***	−0.012	−3.27***	0.033***	−0.004	−3.51***
	(3.33)	(−0.78)		(3.57)	(−0.83)	
Nasdaq 100	0.026	−0.111***	−3.92***	0.007	−0.035***	−3.80***
	(1.32)	(−3.84)		(1.05)	(−4.04)	
NYSE	0.078***	−0.104***	−4.10***	0.022***	−0.037***	−4.24***
	(4.18)	(−2.59)		(4.22)	(−2.89)	
Russell 2000	0.138***	−0.097***	−5.46***	0.048***	−0.034***	−5.56***
	(6.35)	(−2.60)		(5.41)	(−2.90)	
S&P 400	0.066***	−0.067**	−3.81***	0.018***	−0.025***	−3.67***
	(3.63)	(−2.25)		(2.84)	(−2.54)	
KOSPI 200	0.033	−0.013	−1.32	0.006	−0.007	−1.02
	(1.10)	(−0.74)		(0.55)	(−1.11)	
Panel of indexes	0.054***	−0.062***	−4.27***	0.017***	−0.023***	−4.35***
	(3.82)	(−2.68)		(3.56)	(−2.91)	
Panel of indexes (one-day lag)	0.001	-0.057**	−2.17**	0.002	−0.019**	−2.39**
	(0.07)	(−2.41)		(0.38)	(−2.50)	

Table 1 summarizes international evidence regarding short-term index serial dependence in daily index returns for all of the indexes in our sample. As a starting point, we measure serial dependence through conventional AR(1) coefficients for both daily and weekly returns. We report AR(1) coefficients with Newey-West corrected standard errors for individual indexes and with standard errors double-clustered in the time and index dimension for all indexes combined (rows labeled "Panel of indices").

Before 1999, first-order serial dependence is positive for all indexes in our sample, which is well known from prior work. The daily AR(1) coefficients are significantly positive for 16 of the 20 indexes. The bottom rows show this result also holds when looking across all individual indexes in a panel setup. Serial dependence becomes indistinguishable from zero when using a one-day implementation lag, to mitigate the impact of nonsynchronous trading and other microstructure biases (Jegadeesh, 1990).

In stark contrast, first-order daily autocorrelation turns negative for 16 out of 20 indexes in the post-1999 subsample. The coefficients are significantly negative for seven of 20 indexes and for the panel of indexes both with and without the one-day implementation lag. Column 3 labeled "t(diff.)" shows that the decline in AR(1) coefficients between the two subsamples is significant in 17 of the 20 indexes and across the cross section of indexes (without implementation lag).

The decline in serial dependence is not limited to daily, or first-order, autocorrelations. We observe a similarly declining trend in serial dependence at the weekly frequency, with weekly AR(1) coefficients in Table 1 turning negative for all 20 indexes in the post-1999 subsample. Moreover, weekly AR(1) coefficients decline between the two subsamples for 18 of the 20 indexes and nine such declines are significant. Finally, Fig. 3 plots daily pth-order autocorrelations during the before and after subsamples for p up to 21. The plot shows that serial dependence has declined across most lags and has turned significantly negative for p equal to one, two, three, and five.

Overall, based on conventional autocorrelation measures in an extended sample period, index serial dependence used to be positive but has significantly decreased over time. In recent years, it switched sign to become significantly negative.

3.2. Multi-period serial dependence

What is the best way to measure short-term serial dependence in returns? Given a measure for serial dependence, what order and frequency should one focus on? A priori, the answers are not clear, but the analysis by Richardson and Smith (1994) provides useful guidance. Richardson and Smith (1994) demonstrate that many serial dependence statistics are linear combinations of autocorrelations at various lags but differ in terms of the weights placed on these lags. Their analytical and simulation results suggest that against a reasonable mean-reversion alternative to the random walk hypothesis, statistics that place declining weights on higher-order autocorrelations are generally more powerful. Mean reversion can be in either stock prices (e.g., Fama and French, 1988; Richardson and Smith, 1994) or stock returns (e.g., Conrad and Kaul, 1988; Lo and MacKinlay, 1988) and fits well with this paper's main finding that serial dependence has turned negative.

Motivated by these results, we propose two novel measures that place declining weights on multiple lags. The first measure, multi-period autocorrelation (MAC(q)), is derived from the difference in variances of returns over different time intervals. Consequently, it can be directly mapped into the standard variance ratios that place linearly declining weights on higher-order autocorrelations (Richardson and Smith, 1994). To see how MAC(q) is directly linked to serial dependence, consider a short (e.g., one week) period of length T, divided into q intervals of equal length (e.g., five trading days), and a return from time 0 to T that equals the sum of the log returns $r_t, t = 1, \ldots, \frac{T}{q}$ with $\mathrm{E}(r_t) = \mu_t = 0$. Serial dependence can simply be measured by the difference between the single-interval variance, Var(T, 1), and the q-interval variance, Var(T, q),

$$\mathrm{Var}(T, 1) - \mathrm{Var}(T, q) = 2\sum_{l=1}^{q-1}(q-l)\mathrm{Cov}(r_t, r_{t-l}) \tag{1}$$

In Appendix B, we demonstrate that the variance difference in Eq. (1) is equivalent to a simple trading strategy that replicates return autocovariances.[3] To comprehensively capture serial dependence in one week of daily returns, so that $q = 5$, Appendix B shows that we can take a position based on past index returns, $4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4}$. The daily return on this position is simply $r_t(4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4})$, which is (in expectation) a weighted sum of autocovariances that we scale into autocorrelations,

$$\mathrm{MAC}(5)_t = r_t(4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4})/(5\cdot\sigma^2), \tag{2}$$

where MAC(5) stands for multi-period autocorrelation with q equal to 5. Facilitating comparison across time and indexes, the full sample variance scaling $q\cdot\sigma^2$ allows us to interpret MAC(5) as a weighted average of autocorrelations from lag 1 to lag 4, with positive (negative) returns being a reflection of positive (negative) serial dependence over the return measurement interval. Clearly, this scaling adjustment does not affect statistical inference. In our empirical analysis, because MAC(5) is computed every day using daily returns over the past week, we correct for autocorrelation in single-index regressions using Newey-West standard errors and in panel regressions by using double-clustered standard errors.

Because MAC(q) is a trading strategy that exploits serial dependence, profits from MAC(q) (that can be tracked in real time) directly reflect the economic relevance of serial dependence in index returns. By contrast, traditional serial dependence tests based on variance ratios or individual AR terms have no direct economic meaning. Also, for $q = 2$, MAC(2) corresponds to $\frac{1}{2}$AR(1), so that the framework above incorporates the conventional AR(1) statistic as a special case.

The second measure is also motivated by Richardson and Smith (1994), who demonstrate that serial dependence statistics with weights that exponentially decline for higher-order autocorrelations can be even more powerful. For this reason, we consider exponentially declining multi-period autocorrelation [EMAC(q)]. We define EMAC(q) as

$$\begin{aligned}\mathrm{EMAC}(q)_t &= r_t\cdot f(\lambda_q, r_{t-\tau})/\sigma^2, \tau = 1, \ldots, \infty,\\ f(\lambda_q, r_t) &= \lambda_q r_t + (1-\lambda_q)f(\lambda_q, r_{t-1}).\end{aligned} \tag{3}$$

Eq. (3) defines f(.) recursively, resulting in an infinite number of exponentially declining lags. Empirically, we scale f(.) by the sum of weights over all lags to ensure they sum to one. Because q in MAC(q) is determined exogenously,

[3] Variance differences and variance ratios are central statistics in the literature on serial dependence. See Campbell et al. (1997) (1997; Chapter 3) for an introduction of the key concepts, and O'Hara and Ye (2011) and Ben-David et al. (2018) for recent use.

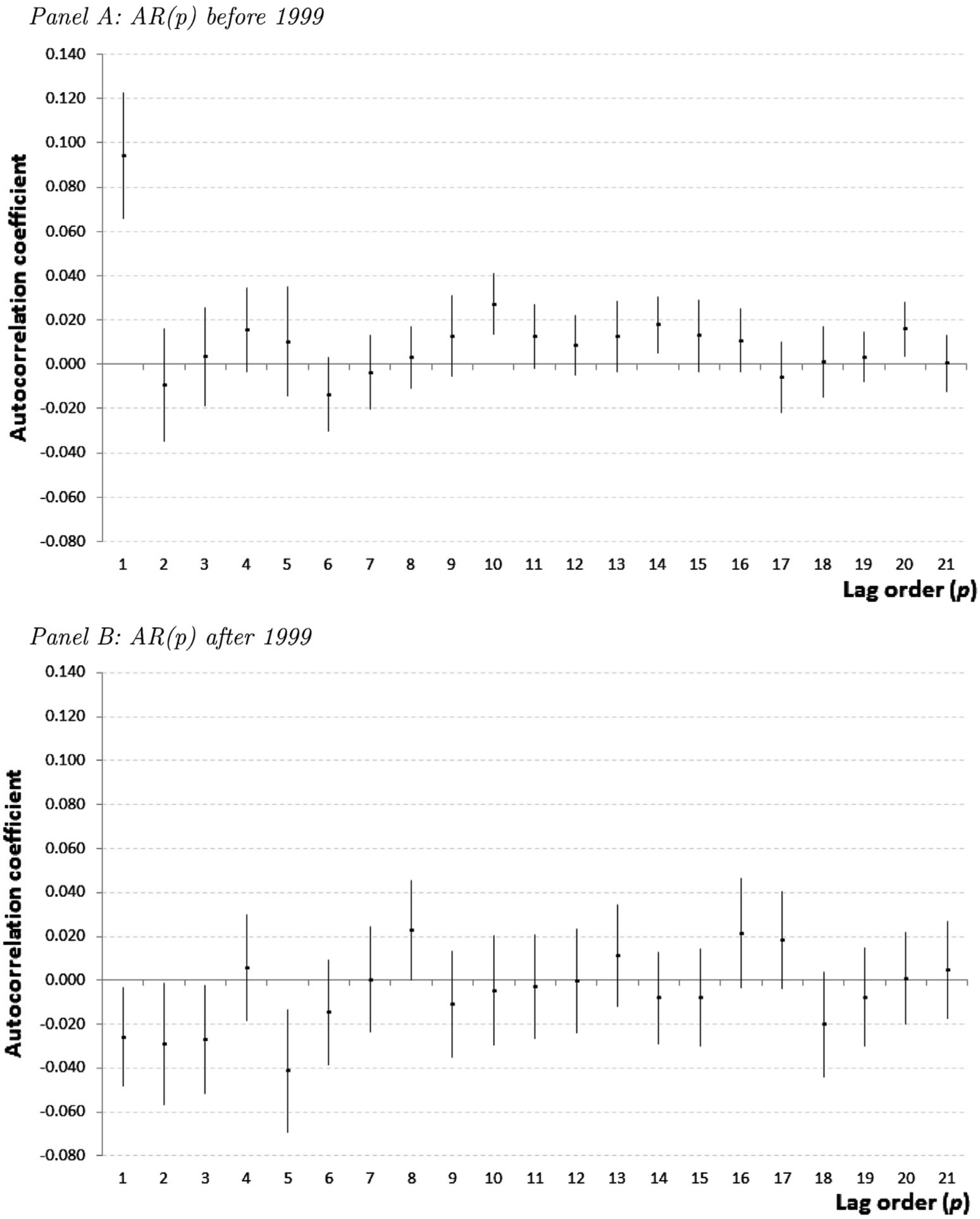

Fig. 3. Recent changes in serial dependence for different lag orders. This figure plots autocorrelation coefficients for our panel of stock market indexes across the world, for different lag orders (p) before and after March 3, 1999. We repeat the analysis in the penultimate row of Table 1 at the daily frequency, and calculate daily autocorrelations separately for lag order 1 (i.e., 1 day) to 21 (i.e., 1 month). The ranges centered around each AR(p) coefficient represent its corresponding 90% confidence interval.

we compare the MAC(q) and EMAC(q) measures using the parameter λ_q, which is chosen such that the half-life of EMAC(q) (the period over which 50% of all weights are distributed) is equal to the half-life of MAC(q).

Table 2 confirms the dramatic decline in serial dependence using both MAC(5) and EMAC(5). Average MAC(5) before 1999 is positive for 19 out of the 20 indexes and significantly so for 11 of them. By contrast, MAC(5) after 1999 is negative for all indexes and significantly so for 13 of the 20 indexes. The change in MAC(5) is significant in 16 of the 20 indexes.

We find virtually identical results when comparing EMAC(5) with MAC(5), indicating that the assigned weights in MAC(5) are very close to the optimal weights in EMAC(5) and that MAC(5) efficiently combines autocorrelations at multiple lags. Hence, we focus on MAC(5) when presenting results in the remainder of the paper, given that it maps into the familiar variance ratio tests and also has a convenient trading strategy interpretation. In the Online Appendix, we further demonstrate the similarity of our results when using either MAC(q) or EMAC(q) definitions and for lag orders varying from one day up to one month of returns (i.e., $q = 2$ up to $q = 22$).

4. Serial dependence and indexing

In this section, we use MAC(5) to further analyze how serial dependence in index returns varies over time and in the cross section. We present evidence that the large negative changes in index serial dependence are associated with the increased popularity of index products. Index MAC(5) is positive up to the introduction of the futures and becomes significantly negative thereafter. This pattern can be found in nearly all indexes in our sample even though their futures are introduced over a time span of almost two decades. MAC(5) is also significantly negative in futures returns and ETFs returns since the introduction of futures and ETFs, respectively. We use the percentage of assets allocated to index products as a measure for the extent of indexing and find a significantly negative relation with serial dependence in both the time series and the cross section.

4.1. Serial dependence and futures introductions

Figs. 1 and 2 show that index serial dependence became negative as index products increased in popularity around the world. However, the correlation between indexing and negative serial dependence could simply reflect a common time trend. An important advantage of our study is its broad coverage of 20 major market indexes. Considerable cross-market variation exists in the starting date of indexing. The cross-sectional dimension helps to isolate the link between indexing and index serial dependence.

We first determine the break date at which each index's serial dependence changes the most using a purely statistical, data-driven approach. For each index, we run cumulative sum (CUSUM) break tests and retrieve the break date from the data as the date at which the cumulative sum of standardized deviations from average MAC(5) is the largest. We ignore any breaks in October 1987 and September 2008, which are characterized by extreme market turmoil, and report results in the first column of Table 3. Removing these two extreme episodes from other parts of our empirical tests does not alter our results in any significant way. The asterisks indicate that the change in $\mathrm{MAC}(5)_{Index}$ around the break date is significant for 15 out of the 20 indexes. A large variation exists in the break dates across the 20 indexes.

We next examine whether the variation in break dates can be explained by the variation in the starting date of indexing. Although the first index fund has been around since December 31, 1975, a long time passed before index funds became popular.[4] Thus, we regard the introduction of futures contracts as the start of indexing and report the futures introduction dates in the second column of Table 3. Comparing the break dates with futures introduction dates, a structural break in serial dependence generally happens just a few years after index futures are introduced. Break dates that occur before or many years after the futures introduction tend to indicate insignificant breaks. A regression of break dates on futures introduction dates produces a positive and highly significant slope coefficient (t-value = 3.17) and an R-squared of 0.36. We present this regression including the raw data in Panel A of Fig. 4.

Panel B presents additional evidence by plotting cumulative MAC(5) (i.e., cumulative serial dependence trading profits) across all equity indexes, futures, and ETFs over our sample period. The horizontal axis is in event time and plots the years between the calendar date and the futures introduction date [for index MAC(5) and futures MAC(5)] or the ETF introduction date [for ETF MAC(5)]. Cumulative serial dependence in index returns clearly has an inverse U-shape that centers around the various futures introductions. Cumulative index MAC(5) is increasing in the years prior to the 20 futures introductions, indicating positive serial dependence. After the introduction, cumulative index MAC(5) decreases, indicating negative serial dependence. The tipping point across all indexes lies within five years after the futures introductions.

In Columns 3 and 4 of Table 3, we directly estimate the impact of futures introductions on serial dependence by regressing index MAC(5) on a dummy variable, D_{intro}, that is equal to one if at least one equity futures contract is introduced on the respective index and zero otherwise,

$$\mathrm{MAC}(5)_{Index,t} = b_1 + b_2 \cdot D_{intro,t} + \varepsilon_t, \tag{4}$$

for each of the 20 indexes. When examining individual indexes, Eq. (4) is a time series regression with Newey-West–corrected standard errors. When examining the pooled sample of indexes, Eq. (4) is a panel regression with standard errors double-clustered (across indexes and over time).

Table 3 reports these results along with simple averages for $\mathrm{MAC}(5)_{futures}$ and $\mathrm{MAC}(5)_{ETF}$ (for which D_{intro} is always equal to one). The intercept term b_1 is positive for 17 indexes and significant for 11 of them, suggesting positive serial dependence before the futures introduction consistent with the papers that examine periods up to the 1990s. The dummy coefficient b_2 measures the change in serial dependence after the futures introduction, which is negative for all 20 indexes with 15 of them significant. The sum of both coefficients $(b_1 + b_2)$ measures index MAC(5) after the futures introduction, which is negative for 17 out of the 20 indexes and significant for nine. Because futures introductions occur between 1982 and 2000, these findings are unlikely to be driven by a single event. In addition, index products experience negative serial dependence right away, from the moment they are introduced. Average $\mathrm{MAC}(5)_{futures}$ is negative for each of the 20 indexes and significant for 12 of them. Similarly, $\mathrm{MAC}(5)_{ETF}$ is negative for

[4] For instance, John C. Bogle, founder of Vanguard, recounts that the road to success was long and winding for the company: "[I]n the early days, the idea that managers of passive equity funds could out-pace the returns earned by active equity managers as a group was derogated and ridiculed. (The index fund was referred to as Bogle' s Folly.)" (Bogle, 2014 p. 46).

Table 3
Breaks in serial dependence.
This table presents results on structural breaks in serial dependence for all stock markets in our sample. Endogenously determined structural break dates in index MAC(5) ("$MAC(5)_{Index}$ break date") are based on the maximum cumulative sum (CUSUM) of deviations from each index's average MAC(5) after excluding October 1987 and the 2008 financial crisis. Asterisks in this column indicate significance of a test against the null hypothesis that the break around the break date results from a Brownian motion. We also report the date at which the first corresponding index futures started trading ("Futures start date"). The columns labeled "$MAC(5)_{Index} = b_1 + b_2 \cdot D_{intro}$" show the results of regressing daily returns on index MAC(5) against the intercept and a futures introduction dummy that equals one after the futures introduction date and zero otherwise (coefficients b_1 and b_2 are reported in percentages). Average futures MAC(5) ("$MAC(5)_{futures}$") and average Exchange Traded Fund (ETF) MAC(5) ("$MAC(5)_{ETF}$"; with corresponding ETF introduction dates) are calculated since the futures or ETF introduction date, respectively. The row labeled "Panel of indexes" reports results from a pooled regression across all of the individual indexes in an equal-weighted panel. The last row ["Panel of indexes (1-day lag)"] applies a one-day implementation lag between current and past returns [i.e., $MAC(5) = r_t(4r_{t-2} + 3r_{t-3} + 2r_{t-4} + 1r_{t-5})/5\sigma^2$]. Reported t-values (in parentheses) are based on standard errors that are Newey-West corrected for individual indexes and double-clustered across indexes and time when all indexes are pooled together. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$MAC(5)_{Index}$ break date	Futures start date	$MAC(5)_{Index} = b_1 + b_2 \cdot D_{intro}$ b_1	b_2	$MAC(5)_{futures}$ Average	$MAC(5)_{ETF}$ Start date	Average
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
S&P 500	8/14/87***	4/22/82	0.085***	−0.165***	−0.091**	01-29-93	−0.087***
			(7.12)	(−5.25)	(−2.49)		(−3.49)
FTSE 100	9/2/98***	5/3/84	−0.008	−0.021	−0.043***	04-28-00	−0.109***
			(−1.35)	(−1.17)	(−2.67)		(−3.18)
DJESI 50	1/7/00	6/22/98	−0.001	−0.070**	−0.070***	03−21-01	−0.065***
			(−0.08)	(−2.51)	(−3.67)		(−3.30)
TOPIX	11/30/93***	9/5/88	0.090***	−0.086***	−0.049***	07-13−01	-0.032
			(6.38)	(−2.67)	(−2.61)		(−1.25)
ASX 200	10/29/97	5/3/00	0.017	−0.061*	−0.036	08-27−01	-0.055**
			(0.76)	(−1.78)	(−1.54)		(−2.26)
TSE 60	4/17/00***	9/7/99	0.098***	-0.177***	−0.061***	10-04-99	-0.047**
			(5.33)	(−4.92)	(−2.84)		(−2.06)
CAC 40	3/07/00*	12/8/88	0.071	−0.113	−0.049***	01-22−01	−0.062***
			(0.77)	(−1.21)	(−3.23)		(−2.81)
DAX	1/29/87	11/23/90	0.022	−0.058**	−0.021	01-03-01	−0.020
			(1.58)	(−2.20)	(−1.18)		(−0.90)
IBEX 35	9/2/98***	4/20/92	0.151**	−0.167**	-0.036**	10-03-06	−0.034
			(2.38)	(−2.52)	(−2.10)		(−1.31)
MIB	9/24/01	11/28/94	0.110*	−0.133**	−0.017	11-12-03	−0.014
			(1.94)	(−2.24)	(−1.00)		(−0.60)
AEX	5/26/86	10/26/88	−0.012	−0.009	−0.028	11-21-05	−0.036
			(−0.33)	(−0.24)	(−1.59)		(−1.36)
OMX Stockholm	4/6/00***	1/2/90	0.073	−0.090*	−0.059***	04-24-01	−0.079***
			(1.56)	(−1.80)	(−3.82)		(−3.15)
SMI	3/24/03	11/9/90	0.008	−0.009	−0.012	03-15-01	−0.036
			(0.12)	(−0.13)	(−0.62)		(−1.46)
Nikkei 225	10/2/90***	9/5/88	0.058***	−0.132***	−0.055***	07-13-01	−0.050*
			(4.30)	(−4.31)	(−2.88)		(−1.92)
HSI	12/25/87**	5/6/86	0.137***	−0.135***	−0.015	11-12-99	−0.039*
			(3.56)	(−3.25)	(−0.52)		(−1.88)
Nasdaq 100	9/1/98**	4/11/96	0.043**	−0.143***	−0.073***	03-10-99	−0.077***
			(2.09)	(−4.36)	(−3.28)		(−3.29)
NYSE	8/14/87***	5/6/82	0.138***	−0.182***	−0.100	04-02-04	−0.069*
			(7.77)	(−5.77)	(−2.43)		(−1.91)
Russell 2000	4/17/00***	2/4/93	0.155***	−0.202***	−0.049**	05-26-00	−0.064***
			(5.53)	(−5.02)	(−2.22)		(−2.77)
S&P 400	1/15/99**	2/14/92	0.141***	−0.173***	−0.048**	05-26-00	−0.041
			(2.79)	(−3.15)	(−2.01)		(−1.63)
KOSPI 200	11/17/99	5/3/96	0.007	−0.002	−0.018	10-14-02	−0.024
			(0.34)	(−0.08)	(−0.96)		(−1.00)
Panel of indexes			0.072***	−0.108***	−0.047***		−0.054***
			(4.55)	(−5.01)	(−3.16)		(−2.94)
Panel of indexes (one-day lag)			0.018	-0.065***	−0.044***		−0.046**
			(1.41)	(−3.41)	(−2.87)		(−2.42)

all indexes and significantly so for 12 of them, with values slightly more negative than for $MAC(5)_{futures}$.

In the bottom rows of Table 3, we run a panel regression across all markets of either the $MAC(5)_{Index}$, $MAC(5)_{futures}$, or $MAC(5)_{ETF}$ series, with standard errors clustered at the time and index level as in Table 3. Global $MAC(5)_{Index}$ is significantly positive prior to the futures introduction (0.072 with t-value = 4.55) and reduces substantially and significantly after the introduction (−0.108 with t-value = −5.01) to a significantly negative −0.036 (t-value = −2.11). Similarly, the coefficients on $MAC(5)_{futures}$ and $MAC(5)_{ETF}$ are significantly negative when pooled together across indexes. In unreported results, we re-run Eq. (4) after creating separate dummy variables for fu-

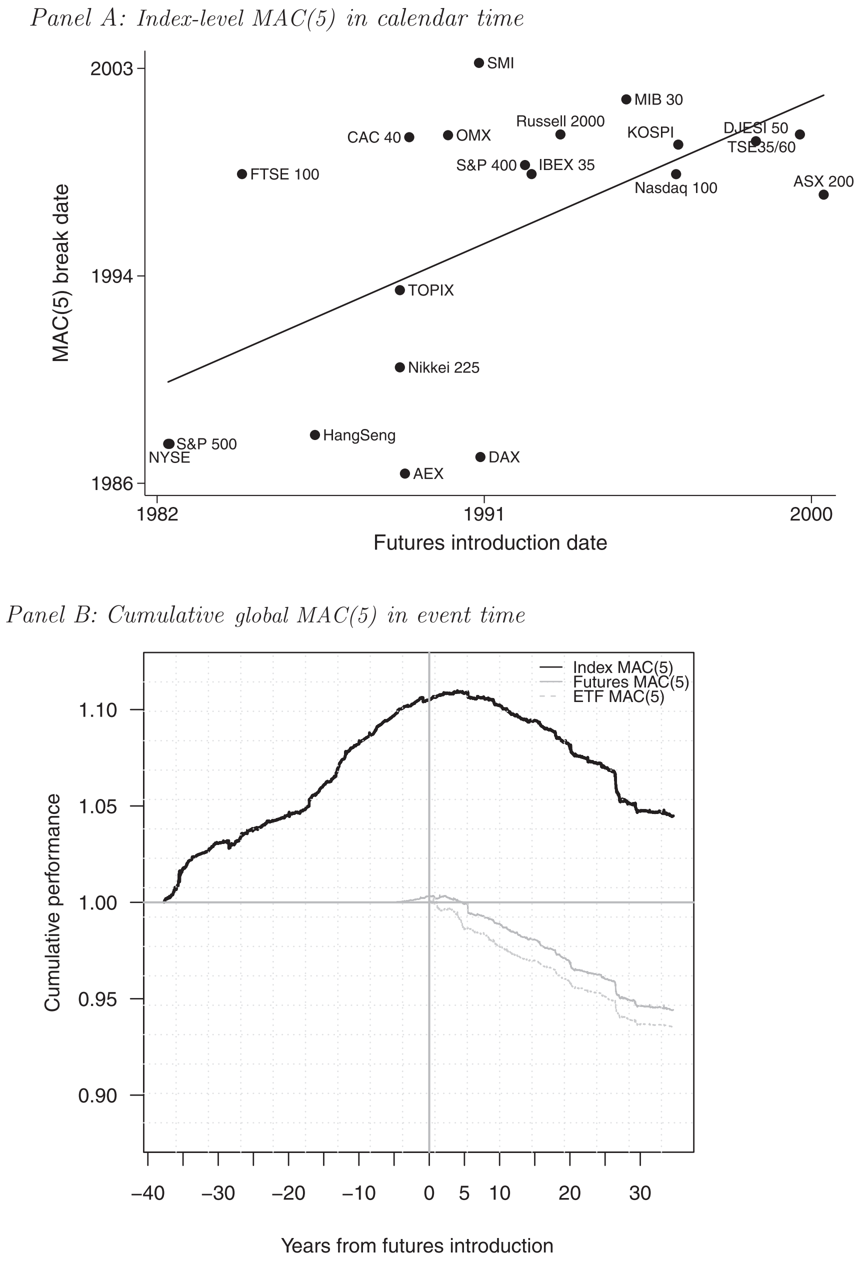

Fig. 4. Serial dependence and the start of indexing. This figure plots serial dependence dynamics against the start of indexing in calendar time (Panel A) and in event time (Panel B). For each index, indexing starts on the day that the first corresponding equity index futures contract was introduced. Panel A plots endogenously determined break points in serial dependence against the start of indexing. The fitted line is based on a linear regression of the MAC(5) break date on the indexing start date. Panel B plots cumulative index MAC(5) (normalized to start at one) around the start of indexing for all indexes combined. The horizontal axis reflects event time, with $t = 0$ reflecting the indexing start date. The black line plots (equally weighted) cumulative index MAC(5), and the gray solid line and gray dashed line plot cumulative futures MAC(5) and exchange-traded fund (ETF) MAC(5), respectively.

tures introductions and ETF introductions. Coefficients on these variables are −0.060 and −0.080 (t-value = −3.86 and −2.91), respectively.[5]

The MAC(q) measure is estimated from a trading strategy that can be executed in real time. The trading strategy allows us to demonstrate that negative serial

[5] Also, Etula et al. (2015) argue that month-end liquidity needs of investors can lead to structural and correlated buying and selling pressures of investors around month-ends, thereby causing short-term reversals in equity indexes. We verify that the above results are robust to these patterns. When we include separate dummy variables for the three periods around month-ends most likely subject to buying and selling pressures (i.e., t-8 to t-4, t-3 to t, and t+1 to t+3) and their interaction with the futures introduction dates of each market, we find coefficients of 0.071 (t-value = 4.29) on the intercept and -0.107 (t-value = -4.87) on the futures introduction dummy.

dependence in index returns is economically important. For instance, a strategy that trades against the negative MAC(5) using all indexes (the S&P 500 alone) in our sample would result in an annualized Sharpe ratio of 0.63 (0.67) after March 2, 1999. Similar Sharpe ratios are observed for the indexes and ETFs. These Sharpe ratios compare favorably against the average Sharpe ratio across the stock markets in our sample of 0.36 and highlight the economic importance of negative index serial dependence. At the same time, trading against negative serial dependence requires frequent rebalancing. As a result, the strategy might not be exploitable to many investors after accounting for transaction costs.

In sum, the introduction of indexing correlates negatively with index serial dependence. We observe positive serial dependence up to the introduction of index products, but economically strong and significantly negative serial dependence in index and index product returns thereafter.

4.2. Serial dependence and the extent of indexing

Thus far, we have used cross-market variation in the introduction of the futures contracts, which is measured by a dummy variable. Next, we examine the relation between serial dependence and several continuous measures of indexing based on the assets allocated to index products as a percentage of the underlying index's market capitalization.

To measure indexing in futures, we multiply the futures open interest (in contracts) with contract size and underlying index price. To mitigate the impact of spikes in futures open interest around roll dates, we average this measure using a three-month moving window that corresponds to the maturity cycle of most futures contracts. To measure ETF indexing, we take the size of the ETF market listed on an index (market capitalization). Both the futures measure and the ETF measure are scaled by daily market capitalization of the underlying index. To measure total indexing, we take the sum of both measures. We exclude the Russell 2000, S&P 400, and NASDAQ indexes because open interest data on the futures from either Bloomberg or Datastream are available only four to ten years after the futures introduction (this does not affect our results). Panel B of Fig. 2 shows that the past 30 years have seen a substantial rise in indexing globally, which coincides with declining serial dependence in the index.

More formally, we regress each index i's MAC(5) on the extent of indexing,

$$\mathrm{MAC}(5)_{index,it} = b_1 + b_2 \cdot Indexing_{it-1} + \theta' \mathbf{X}_{it-1} + \varepsilon_{it}, \quad (5)$$

where the vector $\mathbf{X}_{it}$ contains the TED spread and each index's market volatility, past market returns, and detrended market volume as control variables in the spirit of Nagel (2012), Hameed et al. (2010), and Campbell et al. (1993), respectively. More details on these variables' definitions can be found in Appendix A. We measure indexing over the previous day, but results are practically identical when indexing is measured at time t or $t-5$. Table 4 presents results of a panel regression indicating a significantly negative relation between index serial dependence and indexing. The coefficient of −3.131 with a t-value of −2.90 implies that every 1% increase in indexing decreases serial dependence by about 0.031. In fact, the point at which serial dependence equals zero can be computed for the regressions $\mathrm{MAC}(5)_{index} = b_1 + b_2 \cdot Indexing + \varepsilon$ as the level of indexing at which the regression line crosses the vertical axis [i.e., $\mathrm{MAC}(5)_{index} = 0$]. Globally, this point lies at 1.4% of index capitalization as shown in the the row labeled "Zero serial dependence point."

The effect is similar when we include index fixed effects to control for unobserved differences in indexing between stock markets. The coefficient on indexing remains of very similar size and significance at the 5% level once we include the controls. Coefficients on detrended volume and last month's index volatility are unreported, but they are in line with those in Campbell et al. (1993) and Nagel (2012). When separating futures indexing from ETF indexing, the coefficient on futures indexing becomes larger (−3.617) and remains significant at the 5% level, and the coefficient on ETF indexing becomes larger (−5.283) but with a smaller t-value of −1.76.[6]

To remove any index-specific time trend, we reestimate Eq. (5) in differenced form,

$$\Delta \mathrm{MAC}(5)_{index,it} = b_1 + b_2 \cdot \Delta Indexing_{it-1} + \theta' \boldsymbol{\Delta} \mathbf{X}_{it-1} + \varepsilon_{it}, \quad (6)$$

where differences are calculated over a three-month interval to correspond with the futures rolling cycle. Columns 6–8 of Table 4 indicate that the relation between changes in indexing and changes in index MAC(5) becomes more significant, both economically and statistically. Thus, our results do not seem to reflect latent variables (potentially index-specific) that share a time trend. Because the average change in MAC(5) possibly varies across indexes, which could affect coefficient estimates, we demean the differences from Eq. (6) by adding index fixed effects to the regression. Adding index fixed effects hardly affects any of the coefficients, which reassures us that the increase in indexing has a significantly negative impact on index serial dependence.

Finally, to further address concerns about a common time trend between serial dependence and indexing, we examine this relation cross-sectionally. We focus on the post-1990 period, because before 1990, more than half of the indexes in our sample did not have exposure to index products. Fig. 5 demonstrates that, when we plot average MAC(5) against the average indexing measure across the indexes in our sample, a significantly negative relation emerges (t-value = −2.00). In other words, a higher level of indexing exposure is associated with more negative serial dependence across different markets.

We also run Fama-MacBeth cross-sectional regressions of MAC(5) on the total indexing measure, as reported in

[6] To examine indexing in the broadest sense, we also consider indexing by index mutual funds that seek to fully replicate the S&P 500 using the CRSP Survivorship-Bias-Free US Mutual Funds Database (which covers only the US). To focus strictly on index funds, we ignore all funds that track substantially more or less stocks than all five hundred index constituents. The coefficient on total indexing continues to be significant when we measure indexing by the combined assets in futures, ETFs, and index mutual funds.

Table 4
Index serial dependence and indexing.
This table presents the results of regressing index MAC(5) against indexing measures and controls. All explanatory variables are lagged one day. The estimation sample begins on January 11, 1971, except for the Fama-MacBeth regressions that start in 1991 when at least half of the stock markets in our sample are indexed. We exclude the NASDAQ, NYSE, and Standard & Poor's (S&P) 400 indices because open interest data from either Bloomberg or Datastream are available only four to ten years after the futures introduction. Indexing is measured as total dollar open interest on futures contracts divided by index market capitalization (*Indexing (futures)*), total ETF market capitalization divided by index market capitalization (*Indexing (ETFs)*), or the sum of these two (*Indexing (futures+ETFs)*). In the columns labeled "MAC(5)$_{index}$" we measure index MAC(5) in levels. In the columns labeled "ΔMAC(5)$_{index}$" we take the three-month change in the dependent variable and the independent variables because the futures rolling cycle is typically three months. The column labeled "Fama-MacBeth (>1990)" runs Fama-MacBeth regressions in the cross section of indexes. Control variables (in levels or in differences; included but not tabulated) are log index trading volume detrended with one-year average log index trading volume, the average return over the past 21 trading days, the annualized realized index volatility over the past 21 trading days, and the TED spread defined as spread between three-month London Interbank Offered Rate (LIBOR; or eurodollar rate when unavailable) and the three-month T-bill rate. For the regression $\text{MAC}(5)_{index} = b_1 + b_2 \cdot \textit{Indexing} + \varepsilon$, we can calculate the zero serial dependence point as the level of indexing at which $\text{MAC}(5)_{index} = 0$, i.e., $-b_1/b_2$. Reported t-values (in parentheses) are based on standard errors that are double-clustered across indexes and time or, in case of Fama-MacBeth regressions, Newey-West corrected. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	MAC(5)$_{Index}$					ΔMAC(5)$_{Index}$			Fama-MacBeth (>1990)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.043**	0.020	0.198*	0.195*	0.177	0.002	0.002	0.001	−0.003
	(2.46)	(1.88)	(1.74)	(1.73)	(1.66)	(0.11)	(0.12)	(0.06)	(−0.20)
Indexing (futures+ETFs)	−3.131***	−3.186***	−2.789**						−1.792***
	(−2.90)	(−2.77)	(−2.04)						(−4.64)
Indexing (futures)				−3.617**					
				(−2.06)					
Indexing (ETFs)					−5.283*				
					(−1.76)				
Δ*Indexing (futures+ETFs)*						−9.913***	−9.932***	−6.562***	
						(−2.64)	(−2.63)	(−2.49)	
Controls	No	No	Yes	Yes	Yes	No	No	No	No
ΔControls	No	No	No	No	No	No	No	Yes	No
Index fixed effects	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No
R^2(percent)	0.051	0.060	0.213	0.213	0.195	0.008	0.008	0.172	
Zero serial dependence point	0.014								

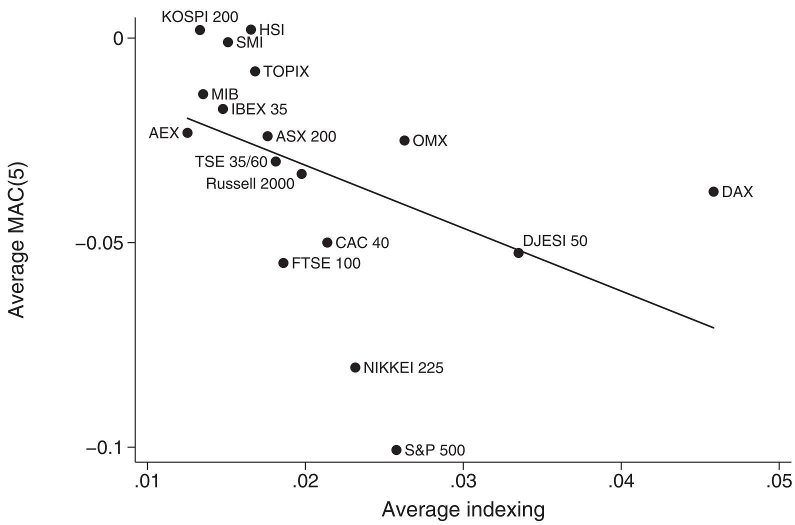

Fig. 5. Serial dependence and the level of indexing. This figure plots serial dependence against indexing for the stock market indexes in our sample. We exclude the NASDAQ, NYSE, and Standard & Poor's (S&P) 400 because open interest data from either Bloomberg or Datastream are available only four to ten years after the futures introduction. Serial dependence is measured as average MAC(5); indexing as average *Indexing (futures+ETFs)* (defined in Table 4). Averages are calculated from 1991 onward, when at least half of the markets in our sample have been indexed. The fitted line results from a linear regression of average index MAC(5) on average indexing.

Column 9 of Table 4. We observe a significantly negative coefficient of −1.792 (t-value = −4.64) on the indexing measure, suggesting that, in the cross-section, a 1% increase in the index measure significantly reduces index serial dependence by about 0.018%.

5. Why did index serial dependence turn negative?

Positive index serial dependence, not surprisingly, was reduced immediately following the introduction of index products. Previous studies show that positive serial dependence results from market microstructure biases such as price staleness and infrequent trading (Fisher, 1966; Scholes and Williams, 1977; Atchison et al., 1987; Lo and MacKinlay, 1990a; Boudoukh et al., 1994, and references cited therein) or lead-lag effects due to a response to economy-wide information that is more sluggish for some stocks than for others (Brennan et al., 1993; Badrinath et al., 1995; Chordia and Swaminathan, 2000; McQueen et al., 1996).[7]

Equity index futures were the first instruments in many countries that offered investors the opportunity to invest in the index easily, cheaply, and continuously during trading hours. This could have improved the functioning of the underlying stock markets in two ways. First, increased responsiveness to market-wide shocks and market makers hedging their inventory position increase trading in the smaller, less liquid index members, which attenuates market microstructure biases such as price staleness.[8] Second, trading in index futures speeds up the incorporation of market-wide information for all stocks in the index so that the lead-lag effect diminishes. These findings imply that index serial dependence decreases to zero after the start of indexing. Returns of index products themselves also should have zero serial dependence because they are traded heavily and continuously throughout the day and unlikely suffer from information asymmetry (Subrahmanyam, 1991; Madhavan and Sobczyk, 2016).

In this paper, we find index serial dependence to not just drop to zero but also turn significantly negative. In addition, serial dependence in index product returns is negative, from the moment these products are traded. Negative index serial dependence suggests the existence of non-fundamental shocks [e.g., price pressure as a compensation for liquidity provision (Campbell et al., 1993; Nagel, 2012)] even at the aggregate level. However, one could argue that aggregate price pressure can come from other factors such as increasing investor demand to trade the market portfolio over time, which affects order flow irrespective of the existence of index products. One could even argue that the futures introduction date is completely endogenous and that futures trading is introduced with the purpose of catering to market-level order flow. To address these concerns, in Section 5.1, we perform a test that directly links the decrease in serial dependence to differential price pressures arising exogenously from the index design. Following Greenwood (2008), we examine how indexing products change serial dependence for small, overweighted Nikkei 225 members relative to large, underweighted Nikkei 225 members.

One could also argue that index-level price pressure has been constantly present over time but used to be overshadowed by stale prices, slow information diffusion, or other factors causing positive serial dependence. Because the introduction of index products eliminates these factors, index serial dependence could have become discernibly negative afterward without actually decreasing. To address this concern, in Section 5.2, we compare how indexing products change serial dependence for an index based on small S&P 500 stocks, relative to a control index of large stocks that are at least as accurately priced and absorb information at least as quickly but are not a member of the S&P 500.

Finally, in Section 5.3, we investigate the important role of index arbitrage in linking serial dependence in index futures or ETFs to serial dependence in the index. In the presence of index arbitrage, the popularity of index products opens up the underlying index to price pressure from these products, and vice versa, thus contributing to the spreading of serial dependence characteristics across markets.

5.1. The Nikkei 225 index versus the TOPIX

The value-weighted TOPIX and the price-weighted Nikkei 225 index are two major equity indexes in Japan that are equally important to investors but differ in their constituent weighting scheme. While the TOPIX is value weighted, the Nikkei 225 index is weighted using the share price of Nikkei 225 member stocks and their par value at the time of offering.

The par value of a common stock (i.e., the monetary amount at which a share is issued or can be redeemed) can be seen as a base for shares and is stated in the corporate charter. Shares cannot be sold below par at an initial public offering (IPO), so that par values indicate the most favorable issue price around an IPO. While this used to be a valuable signal, par value lost its relevance to investors once stock issuance prices were required to be published publicly. Nowadays, in most countries, the par value of stock serves only legal purposes.

In the Nikkei 225, par value for most stocks is 50 yen per share but can also take values of 500, 5,000, or 50,000 yen per share. As a consequence, some of the smaller (larger) stocks receive a relatively large (small) Nikkei 225 weight, which makes them overweighted (underweighted) in comparison with their market capitalization-based weight in the TOPIX. Greenwood (2008) shows that overweighted stocks receive proportionally more price pressure and uses overweighting as an instrument for index demand. Thus, the Japanese market provides an attractive experimental setting to study the effect of indexing on index serial dependence.

To calculate Nikkei 225 index weights, we collect the history of TOPIX and Nikkei 225 index membership from Compustat Global's Index Constituents file. We obtain the

[7] Other explanations are time-varying expected returns (Conrad and Kaul, 1988; Conrad et al., 1991), and contemporaneous correlations between, for example, large caps and small caps and own-portfolio autocorrelations (Hameed, 1997). However, follow-up studies suggest that these explanations do not fully account for positive serial dependence.

[8] So far, we have controlled for market microstructure biases to some extent using the one-day "implementation" lag between the current returns and the weighted sum of past returns in Eq. (2) (i.e., between the formation and holding period). MAC(5) falls into negative territories with and without the implementation lag in both index and the (large and very liquid) futures and ETF markets. Also, MAC(5) is less susceptible to serial dependence coming from stale prices than measures such as AR(1). Furthermore, microstructure biases are unlikely to have a significant impact on serial dependence for any well diversified index (Lo and MacKinlay, 1990a). Finally, when we decompose index-level serial dependence as in Lo and MacKinlay (1990b), both index constituents' serial dependence and their lead-lag effects turn negative. Hence, attenuated microstructure biases are unlikely to explain our key finding.

par values of Nikkei 225 members from Factset, Nikkei, Robin Greenwood's website[9], or (if still unavailable) by assigning par values that minimize the difference between the publicly reported Nikkei 225 index and our replicated Nikkei 225 index. Appendix A describes the data collecting procedure in full detail. The replicated index has a correlation of more than 0.99 with the publicly reported Nikkei 225. Nikkei 225 index weights are defined as

$$w_{jt}^{N225} = \frac{\frac{P_{jt}}{PV_j/50}}{\sum_{k=1}^{225} \frac{P_{kt}}{PV_k/50}}, \tag{7}$$

where PV_j represents member stock j's par value and P_{jt} is its price at time t. Hence, firms are free to choose a certain par value (in addition to choosing the number of shares issued, the float factor, and the price). Because the weights are a function of the current price and the par value at issuance, often many years ago, they are unlikely affected by stock characteristics such as size, volatility, etc., that are possibly shared by index constituents as a result of entering the index.

We follow the approach in Greenwood (2008), which examines the extent to which individual stocks are relatively overweighted in the Nikkei 225 (OW_{jt}) by comparing each Nikkei 225 stock's price-based weight, w_{jt}^{N225}, with its market capitalization-based weight in the value-weighted TOPIX, w_{jt}^{VW}:

$$OW_{jt} = \log\left(1 + \frac{w_{jt}^{N225}}{w_{jt}^{VW}}\right). \tag{8}$$

This measure is equal to zero for non-Nikkei stocks. Greenwood (2008) aggregates stock-level overweighting OW_{jt} to the index level by tracking profits on a zero-investment trading strategy, which pays off when overweighted stocks move more with lagged index returns than underweighted stocks. The idea is that a demand shock makes stocks that are relatively overweighted (underweighted) rise too much (little) after an increase in the index and conversely after a decrease in the index. Consequently, more overweighted stocks should react more strongly in the opposite direction of lagged index returns or, put differently, experience more negative serial dependence. In contrast, the spreading of information would mostly affect large (i.e., underweighted) stocks. Also, if broad developments were to drive our results (such as increasing investor demand to trade the market portfolio), they affect both overweighted stocks and underweighted stocks in a similar way. Hence, this approach allows us to examine how indexing affects serial dependence, independent from other drivers such as information diffusion and broad market-wide developments.

Our first measure is a replication of the strategy in Greenwood [2008, Eq. (19)] with positions multiplied by -1 to bring his reversal measure in line with our paper's interpretation. We compute the weight on each stock j as

$$w_{jt} = \left(OW_{jt-1} - \frac{1}{N}\sum_{n=1}^{225} OW_{nt-1}\right) r_{t-1}^{Nikkei225}. \tag{9}$$

Results based on this weighting scheme are in Columns 3 and 7 of Table 5. Unreported results indicate that cumulative returns based on this strategy are identical to Fig. 5 in Greenwood (2008).

We also consider weights based on multiple lags, similar to the construction of MAC(5):

$$w_{jt} = \left(OW_{jt-1} - \frac{1}{N}\sum_{n=1}^{225} OW_{nt-1}\right) \sum_{l=1}^{q-1} (q-l) r_{t-l}^{Nikkei225}, \tag{10}$$

with $q = 5$. Results based on this weighting scheme are presented in Columns 4 and 8.

We also construct an alternative overweighting measure by sorting stocks each month in five portfolios based on their relative overweighting and replacing the term in parentheses in Eq. (10) by the difference in returns between the high (overweighted) and low (underweighted) portfolio. Results using this measure (labeled "OW-UW Portfolio") are similar to the approach above based on the entire index but use only 20% of the most overweighted and 20% of the most underweighted stocks in determining overweighting.

With two overweighting measures and two lag structures, we calculate returns $\mathcal{R}_t$ on four trading strategies, with $\mathcal{R}_t \equiv \sum_{j=1}^{225} w_{jt} r_{jt}$. All four strategies have the advantage of exploiting variation between index stocks. Such variation ignores the movement of all index stocks combined and adds further evidence against alternative explanations based on market-wide developments that take place over the sample period.

Our sample begins in January 1986, the earliest date for which Nikkei 225 and TOPIX constituents are available in Compustat Global, and consists of 331 stocks that were in the Nikkei 225 index at least one day from 1985 to 2016, and 1,956 stocks that were in the TOPIX (First Section) for at least 60 trading days. Over time, an average of 156 Nikkei 225 stocks (47 Nikkei 225 stocks) have a price-based weight that is larger (smaller) than their value-based weight in the TOPIX and, on average, 53 Nikkei 225 stocks have weights of more than five times their weight in the TOPIX. Cumulative MAC(5) for the Nikkei 225 looks similar to Panel B of Fig. 4, with an inverse U-shape that peaks shortly after the futures introduction.

We regress daily strategy returns against indexing:

$$\mathcal{R}_t = b_1 + b_2 \cdot Indexing_{t-1}^{N225} + \theta' \mathbf{X}_{t-1} + \varepsilon_t, \tag{11}$$

where $Indexing_t^{N225}$ is either a dummy related to the Nikkei 225 futures introduction (D_{intro}^{N225}) or the difference in Nikkei 225 indexing and TOPIX indexing (*Relative indexing (futures+ETF)*). The vector $\mathbf{X}_t$ contains the same set of control variables as before, specifically for the Nikkei 225: market volatility, the TED spread, past market returns, and detrended market volume.

The results presented in Table 5 demonstrate that indexing causes serial dependence to become more negative in a portfolio that is exogenously tilted toward stocks more sensitive to indexing. Coefficients on the intercept indicate

[9] The data were used in Greenwood (2005) and can be downloaded from http://www.people.hbs.edu/rgreenwood/Nikkei225Data.xls.

Table 5
Serial dependence and indexing in overweighted (OW) versus underweighted (UW) Nikkei 225 stocks.
This table presents results based on relative index overweighting in Nikkei 225 stocks after regressing four zero-investment trading strategies against a futures introduction dummy for the Nikkei 225 ("D^{N225}_{intro}") and Nikkei 225 indexing relative to Tokyo Stock Price Index (TOPIX) indexing (*Relative indexing*). *Relative indexing* is total indexing on the Nikkei 225 minus total indexing on the TOPIX, with total indexing and control variables defined as in Table 4. Trading strategy returns are defined as $\mathcal{R}_t \equiv \sum_{j=1}^{225} w_{jt} r_{jt}$, where w_{jt} is a weight assigned to return r on stock j based on the overweighting measure in Greenwood (2008),

$$OW_{jt} = \log\left(1 + \frac{w^{N225}_{jt}}{w^{VW}_{jt}}\right),$$

where w^{N225}_{jt} is the Nikkei 225 price weight and w^{VW}_{jt} is the TOPIX value weight. We determine strategy weight $w_{jt} = A \cdot B$ by calculating $A \equiv \left(OW_{it-1} - \frac{1}{N}\sum OW_{jt-1}\right)$ in the columns labeled "OW Portfolio" or by cross-sectionally sorting stocks every day based on OW_{jt} and calculating A as the difference between the top overweighted quintile and bottom overweighted (i.e., underweighted) quintile (columns labeled "OW - UW portfolio"). Index increases (decreases) B are measured by either $B \equiv r^{N225}_{t-1}$ in the columns labeled "$q = 2$" or by $B \equiv \sum_{l=1}^{4}(5-l) r^{Nikkei225}_{t-l}$ in the columns labeled "$q = 5$." Coefficients are multiplied by 10^4 to facilitate readability. Reported t-values (in parentheses) are based on standard errors that are Newey-West corrected. The rows labeled "*Intercept + futures intro*" sum both coefficients and test against the null that the intercept and futures introduction dummy are zero. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	OW - UW portfolio		OW portfolio		OW - UW portfolio		OW portfolio	
Variable	$q=2$	$q=5$	$q=2$	$q=5$	$q=2$	$q=5$	$q=2$	$q=5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.195	0.055	0.099	0.031	−0.018	0.062	0.074	0.067
	(1.24)	(1.17)	(1.59)	(1.50)	(-0.15)	(0.72)	(1.09)	(1.65)
D^{N225}_{intro}	−0.374**	-0.102**	−0.207***	−0.052**				
	(−2.36)	(−2.11)	(−3.20)	(−2.35)				
Relative indexing					−12.408***	−3.767**	−11.170***	−3.591***
					(−4.12)	(−2.44)	(−4.93)	(−3.18)
Intercept + futures intro	−0.180***	−0.048***	−0.108***	−0.022**				
	(−7.72)	(−3.60)	(−6.40)	(−2.45)				
Controls	No	No	No	No	Yes	Yes	Yes	Yes
R^2(percent)	0.235	0.077	0.174	0.048	0.851	0.549	1.063	0.562

that profits are generally zero before the start of indexing. Hence, until then, overweighted and underweighted stocks did not respond differently to lagged market returns. The coefficients on the Nikkei 225 futures introduction dummy are significantly negative, indicating that serial dependence has decreased more for overweighted stocks since the start of indexing. Furthermore, the sum of coefficients b_1 and b_2 (*Intercept+futures intro*) demonstrates that serial dependence has turned significantly negative since then. The coefficients on the continuous indexing measure are also negative, indicating that the wedge between the two groups' serial dependence widens as the importance of indexing in the Nikkei 225 increases relative to indexing in the TOPIX.

In sum, as Nikkei 225 indexing increases, serial dependence decreases significantly more for overweighted index members than for underweighted members. Because Nikkei 225 weights vary between stocks and are unrelated to stock characteristics except for the current price and the par value at which the stock enters the index, the significant decrease in serial dependence is caused by effects unrelated to market-wide developments (which predicts insignificant coefficients) or the spreading of information (which predicts positive coefficients).

5.2. S&P 500 index versus non–S&P 500 index

Having demonstrated the causal effects of cross-sectional differences in demand between Nikkei 225 member stocks, we present additional evidence from comparing changes in serial dependence between member stocks and nonmember stocks. To this end, we calculate the differential effect of indexing on index serial dependence, depending on whether a stock is a member of the S&P 500 or not.

Ideally, we would like to compare stocks in the S&P 500 index with a matching set of non-S&P stocks that are identical except that they do not have S&P 500 membership. However, because large S&P stocks are issued by the very largest and most well known companies in the US stock market, we cannot construct a portfolio of similar-size (and similarly well tracked) non–S&P 500 stocks. Therefore, we build an index based on the bottom half of the S&P 500 (i.e., the 250 smallest S&P 500 stocks) at the time of the futures introduction. We compare this index with a control index built from the largest US stocks that are not in the S&P 500 at the same time. Both indexes are value weighted so that the methodology is comparable to the construction of the S&P 500. Large non–S&P 500 stocks are much more frequently traded, hardly subject to nonsynchronous trading, and quickly reflect market-wide information in their stock price. Yet, they are not subject to any price pressure coming from being a member of the most important index worldwide.

Panel A of Table 6 demonstrates that large non–S&P 500 stocks are about twice the market size of small S&P 500 stocks and more often traded in terms of average volume. Both groups of stocks have similar turnover and analyst coverage, on average. Because stocks scoring high on these variables tend to incorporate market-wide information

Table 6
Serial dependence and indexing in Standard & Poor's (S&P) 500 stocks versus large non-S&P 500 stocks. This table compares subindex MAC(5) between a portfolio of the 250 stocks in the bottom half of the S&P 500 and a portfolio of the 250 largest stocks that are not in the S&P 500. Panel A summarizes market capitalization, volume, turnover, analyst coverage, and institutional ownership for the stocks underlying each of the two subindexes. In Panel B, we regress subindex MAC(5) on an indicator variable equal to one for observations based on the small S&P 500 member stocks and zero otherwise (*In S&P*), indexing measures specifically for the S&P 500, control variables, and interactions between the *In S&P* variable and each indexing measure. All explanatory variables are as defined in Table 4 and specific to the S&P 500. Reported *t*-values (in parentheses) are based on standard errors that are clustered in the time dimension. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Characteristics of member and non-member stocks

Variable	Smallest 250 stocks in S&P		Largest 250 stocks not in S&P	
	Average	Standard deviation	Average	Standard deviation
	(1)	(2)	(3)	(4)
Market cap (billion of dollars)	2.561	3.384	5.194	11.100
Volume (billion)	0.825	3.227	1.228	7.794
Turnover	5.026	9.580	5.682	24.247
Analyst coverage	14.612	6.825	12.730	7.128
Inst. ownership	0.314	0.344	0.200	0.284

Panel B: Importance of S&P membership for decrease in serial dependence

Variable	Subindex MAC(5)			
	(1)	(2)	(3)	(4)
Intercept	0.174***	0.343	0.360	0.294
	(9.39)	(1.38)	(1.39)	(1.28)
In S&P	0.044***			
	(2.71)			
$D_{intro}^{S\&P500}$	−0.113***			
	(-2.87)			
In S&P×$D_{intro}^{S\&P500}$	−0.156***			
	(−3.66)			
$Indexing^{S\&P500}$		−5.875*		
		(−1.94)		
In S&P × $Indexing^{S\&P500}$		−8.462***		
		(−2.57)		
$Indexing^{S\&P500}(futures)$			−9.586*	
			(−1.79)	
In S&P × $\mathrm{Indexing}^{S\&P500}(futures)$			−14.24**	
			(−2.46)	
$Indexing^{S\&P500}(ETFs)$				−9.154**
				(−2.12)
In S&P × $Indexing^{S\&P500}(ETFs)$				−12.36***
				(−2.63)
Controls	No	Yes	Yes	Yes
Number of observations	23,200	23,200	23,200	23,200
R^2(percent)	0.054	0.246	0.254	0.207

faster (Lo and MacKinlay, 1990b; Chordia and Swaminathan, 2000; Brennan et al., 1993), the large non-S&P stocks can be expected to incorporate information at least as fast as the small S&P 500 stocks, be easier to trade, and be less subject to microstructure noise. Thus, serial dependence should be similar or lower in the large non–S&P 500 subset if it were not for indexing. At the same time, the small S&P 500 stocks have higher institutional ownership, suggesting stronger institutional demand for index stocks.

In Panel B of Table 6, we regress MAC(5) on an *In S&P* dummy equal to one for the small S&P 500 index and zero for the large non-S&P 500 index, interacted with one of our measures for indexing,

$$MAC(5)_{it} = b_1 + b_2 Indexing_{t-1}^{S\&P500} + b_3 In\,S\&P_i + b_4 In\,S\&P_i \times Indexing_{t-1}^{S\&P500} + \theta' \mathbf{X}_{t-1} + \varepsilon_{it}, \quad (12)$$

where MAC(5) captures the return on the two subindexes i and $Indexing_t^{S\&P500}$ is a dummy equal to one after the introduction of indexing and zero otherwise ($D_{intro}^{S\&P500}$, as in Table 3 for the S&P 500) or one of the continuous indexing variables from Table 4 [i.e., *Indexing, Indexing (futures)* and *Indexing (ETFs)* for the S&P 500]. The vector $\mathbf{X}_t$ contains the same set of control variables as before, for the S&P 500: market volatility, the TED spread, past market returns, and detrended market volume. With only two subindexes, standard errors are clustered in the time dimension, but results are similar or better with Newey-West or index-clustered errors.

In Column 1 of Table 6, Panel B, b_1 is significantly positive, indicating that serial dependence is positive for non–S&P 500 firms before the futures introduction. Coefficient b_3 is also significantly positive, indicating that, prior to indexing, portfolio-level serial dependence is higher for the small S&P 500 stocks than for the large non–S&P 500 stocks. This suggests that information diffuses faster across the large, well-traded non–S&P 500 stocks up to the futures introduction.[10] The coefficient on the futures introduction dummy (b_2) indicates that serial dependence for the large non–S&P 500 stocks decreases significantly afterward, from 0.174 to 0.061. However, the coefficient on $In\ S\&P \times D^{S\&P500}_{intro}$ (b_4) shows that this decrease is significantly more negative for the small S&P 500 members. In fact, the sum of $D^{S\&P500}_{intro}$ and $In\ S\&P \times D^{S\&P500}_{intro}$ coefficients ($b_2 + b_4 = -0.269$) indicates that serial dependence steeply decreases for these stocks into negative territory, from $b_1 + b_3 = 0.218$ (higher than for very large nonmember stocks) to $b_1 + b_2 + b_3 + b_4 = -0.051$ (negative and lower than for very large nonmember stocks). This result provides direct evidence against a narrative that demand effects have always led to negative serial dependence in the past but become discernible only once they are no longer offset by factors that lead to positive serial dependence (such as stale prices and slow information diffusion).

Results in Table 6 are similar when we add control variables and use the continuous indexing measures *Indexing*, *Indexing (futures)*, and *Indexing (ETFs)* from Table 4. Coefficients on the level of indexing are negative, indicative of a downward trend in serial dependence as indexing increases. Most importantly, the significantly negative interaction coefficients demonstrate that serial dependence decreases significantly more for the index based on small S&P 500 stocks. Thus, all columns in Table 6 point toward a significant effect of index membership on serial dependence that goes beyond explanations based on faster information diffusion and reduced microstructure noise.[11]

5.3. The index arbitrage mechanism

The fact that serial dependence is negative for both the index and the index product is consistent with the presence of arbitrage between the two. In this section, we examine such index arbitrage in greater detail. Index arbitrage can propagate price pressure from the index product to the underlying index, or vice versa. For instance, Ben-David et al. (2018) argue that for continuously traded index products such as ETFs, index arbitrage channels serial dependence in index products into the underlying index as liquidity providers hedge their exposure to the index products by taking an offsetting position in the underlying index. This adds price pressure to the index stocks in the same direction as for the index product. After the price pressure disappears, the subsequent price reversal generates negative serial dependence in both the index and the index product.

Arbitrage per se says little about the underlying cause of initial price pressure. Yet, as index futures and ETFs become more popular and can be traded continuously throughout the day, price pressure is likely to exist in index product markets and can spread through arbitrage. Consequently, while stock markets used to be exposed to price pressure only from individual stocks before the start of indexing, now they are also exposed to price pressure originating from index products such as futures and ETFs through the arbitrage channel.

If index arbitrage spreads price pressures between the index and the index product, we would expect index MAC(5) to be closely related to index product MAC(5) [i.e., index MAC(5) = $\phi \cdot$ index product MAC(5) with $\phi > 0$]. Furthermore, ϕ should be larger when more arbitrage activity between the index products and the index takes place. To examine the importance of arbitrage, we estimate ϕ and see how it interacts with arbitrage activity. Arbitrage activity is likely to be higher in a market when index products take a larger share of the market. Therefore, we use *Indexing (Futures)* or *Indexing (ETFs)* (measures from Section 5.2) to proxy for arbitrage activity.

We regress weekly index MAC(5) on weekly index product MAC(5) to capture ϕ and its interaction with indexing:

$$MAC(5)_{index,it} = b_1 + \phi_1 MAC(5)_{j,it} + \phi_2 MAC(5)_{j,it} \cdot Indexing_{j,it-5} + \theta Indexing_{j,it-5} + \varepsilon_{it}. \quad (13)$$

with $j = ETF$ or *Futures*. Indexing is measured at the start of the weekly period over which we measure index MAC(5) to avoid overlapping periods. To limit the impact of asynchronous trading times between the futures and the index, we compound daily (index product and index) MAC(5) returns into weekly (Wednesday–Wednesday) returns. As before, different standard error adjustment methods lead to similar standard error estimates. We include level versions of all of the interacted variables and index fixed effects (both unreported).

The stand-alone regression coefficients on futures MAC(5) and ETF MAC(5), presented in Columns 1 and 3 of Table 7, are all positive and highly significant. Thus, index MAC(5) significantly moves together with futures MAC(5) and ETF MAC(5), suggesting the presence of index arbitrage. In Columns 2 and 4, we present results after interacting this variable with *Indexing*. Coefficients on the interaction terms are highly significant and positive for both futures indexing and ETF indexing, indicating that more arbitrage activity brings index MAC(5) significantly closer to futures MAC(5). Therefore, as indexing products grow in relative importance, index arbitrage becomes stronger and negative serial dependence in the index becomes more closely connected to serial dependence in the indexing products.

[10] This coefficient is significant at the 15% level with Newey-West standard errors.

[11] To get some sense of the relative importance of these explanations, we decompose the S&P 500 autocovariance terms from Eq. (2) into the autocovariance of its constituents (i.e., reversals) and cross-autocovariance across constituents (i.e., lead-lag effects) as in Lo and MacKinlay (1990b). We find that, prior to the futures introduction, both the lead-lag effect and the constituent-level reversal effect are significant. The futures introduction has a negative effect on both components that is similar in terms of their relative contributions to total autocovariance. This is also true when we decompose S&P 500 autocovariance into the (cross-)autocovariance of both constituents and sub-portfolios based on size, industry, volume, analyst coverage, or institutional ownership and when we decompose the Nikkei 225 autocovariance into the (cross-)autocovariance of constituents and size or industry sub-portfolios.

Table 7
The index arbitrage mechanism.
This table presents results after regressing weekly (Wednesday-Wednesday) returns on MAC(5)$_{index}$ against weekly returns on MAC(5)$_{futures}$ (columns labeled "$j = Futures$") or MAC(5)$_{ETF}$ (columns labeled "$j = ETF$"), and the interaction variables with futures indexing or exchange traded fund (ETF) indexing, respectively. *Indexing (futures)* and *Indexing (ETFs)* are defined in Table 4. Reported *t*-values (in parentheses) are based on standard errors that are clustered in the time dimension. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Weekly MAC(5)$_{index}$			
Variable	$j = Futures$		$j = ETF$	
	(1)	(2)	(3)	(4)
Weekly MAC(5)$_j$	0.558***	0.202	0.879***	0.861***
	(3.06)	(0.83)	(16.87)	(11.04)
Weekly MAC(5)$_j \times Indexing_j$		23.417***		8.052***
		(2.75)		(2.53)
Level versions of interacted variables	Yes	Yes	Yes	Yes
Index fixed effects	Yes	Yes	Yes	Yes
R^2(percent)	48.9	64.3	81.7	86.4

6. Conclusion

This paper presents a new stylized fact: Serial dependence in daily to weekly index returns around the world was traditionally positive but has turned significantly negative in recent years. We examine short-term serial dependence across 20 major stock market indexes in developed countries. We measure serial dependence via conventional measures and a novel statistic that captures serial dependence over multiple lags and is easy to implement and interpret.

The dramatic change in serial dependence is significantly related to indexing, i.e., the growing popularity of index products such as equity index futures, ETFs, and mutual funds. Around the world, index serial dependence tends to be positive before the introduction of index products, in line with previous studies, but decreases once index products are introduced on the index and eventually turns significantly negative as indexing gains importance. As an index's exposure to index products increases by 1%, serial dependence decreases by about -0.031. Serial dependence in ETFs and futures is negative from the moment these products are launched. Taking advantage of unique features of the Nikkei 225 index weighting scheme and the discontinuity around S&P 500 index membership, we find that negative serial dependence arises because of indexing. Further evidence supports the notion that index arbitrage spreads negative serial dependence between these index products and the underlying index, in line with prior work (e.g., Ben-David et al., 2018; Leippold et al., 2015).

Given the many benefits associated with indexing, the growth in index products can be expected to continue for the next decade. Index investments are commonly advised by government authorities, academics, and market participants as good investment practice. This paper's new result highlights an unexpected side effect to these benefits as negative serial dependence signals excessive price movements even at the index level. Excessive price movement could impose costs on institutional and individual investors who trade often. It could even hurt passive individual investors, as many of them now invest through financial institutions (French, 2008; Stambaugh, 2014). On a more positive note, our results suggest that pro-active investors can enhance their return from opportunistic liquidity provision.

Appendix A. Data construction

Our data set is constructed as follows.

A.1. Equity indexes

Indexes covered are the S&P 500 index (S&P 500), Financial Times Stock Exchange 100 index (FTSE 100), EUROSTOXX 50 Index (DJESI 50), Tokyo Stock Price Index (TOPIX), Australian Securities Exchange 200 Index (ASX 200), Toronto Stock Exchange 60 Index (TSE 60), the Paris Bourse's Cotation Assistée en Continu 40 Index (CAC 40), Deutscher Aktienindex (DAX), Iberia Exchange 35 Index (IBEX 35), Milano Italia Borsa 30 Index (MIB), Amsterdam Exchange Index (AEX), Stockholm Stock Exchange Index (OMX Stockholm), Swiss Market Index (SMI), Nihon Keizai Shimbun 225 Index (Nikkei 225), Hang Seng Index (HSI), Nasdaq Stock Market 100 Index (Nasdaq 100), New York Stock Exchange Index (NYSE), Russell 2000 Index (Russell 2000), S&P MidCap 400 Index (S&P 400), and the Korea Composite Stock Price 200 Index (KOSPI 200).

We obtain data from Datastream and Bloomberg. Our sample begins on January 1, 1951 or when index data became available in one of these sources. The sample ends on December 31, 2016 or when all futures stop trading (this happens only for the NYSE, on September 15, 2011). We collect information on total returns, index prices, dividend yields, and local risk free rates to construct excess index returns, as well as total market capitalization (in local currencies) and daily traded volume. We cross-validate returns computed from Datastream data against those computed from Bloomberg data to correct data errors as much as possible.

A.2. Equity futures

From Bloomberg, we obtain prices from front month futures contracts, which are rolled one day before expiry, to construct futures returns. These contracts are the most liquid futures, generally accounting for over 80% of the trading volume and open interest across all listed contracts on an index. We collect information on futures prices from Datastream to cross-check the Bloomberg futures data, and to backfill Bloomberg's futures returns when not covered by Bloomberg. For the Nikkei 225, we focus on the futures listed in the main market, Osaka. However, results are similar when using contract prices from the Singapore International Money Exchange (SIMEX) and Chicago Mercantile Exchange (CME) listings. In addition, for the SMI, we use futures data from Datastream prior to 1997, as Bloomberg contains many stale quotes and misprints for this index before this date.

We also collect data on futures contract size (in listed currencies per index point), volume, and open interest on the futures and, in the case of the introduction of a mini-futures or multiple listings on an index, we combine these with data on the original listing. As several indexes have multiple futures contracts written on them that vary in terms of maturities and contract specifications (e.g., mini versus regular futures), we obtain all futures series that are written on our indexes. We aggregate these to reflect total volume and open interest, in either local currencies or number of contracts, with the number of contracts proportional to the size of the contract that traded first (e.g., we assign a weight of 1/5 to the S&P 500 mini contract because it trades for $100 per index point and the regular S&P 500 future has a size of $500 per index point). Changes in contract size are retrieved from Datastream, or publicly available online sources, or they are assumed when prices increase or decrease with a factor two or more.

A.3. Futures introductions

For futures introductions, we start with the earliest date that futures data become available in Datastream or Bloomberg. To determine whether we have the oldest existing futures series, we cross-check this earliest date with three sources: Ahn et al. (2002), Gulen and Mayhew (2000), and the website of the Commodity Research Bureau (CRB), http://www.crbtrader.com/datacenter.asp.

A.4. ETFs

Several instances of a single ETF can be traded across different countries or exchanges. To retrieve the set of existing equity index ETFs, we obtain a list of all equity index ETFs on offer from a major broker-dealer and cross-check with a list of all ETFs on offer by another major broker-dealer. We include vanilla ETFs, long and short index ETFs, levered ETFs or vanilla ETFs on a levered index, ETFs with a currency hedge, and all ETFs that are cross-listed. We collect information from Bloomberg on ETF prices, market capitalization, and volume. For each index, we add up the total volume of contracts traded. We also calculate market capitalization across all ETFs on a given index but subtract inverse ETFs that offer short positions in the index and multiply market capitalization for leveraged ETFs with the leverage factor (typically one and a half, two, or three times the index return). To prevent the impact of data entry mistakes on our results, we set ETF observations to missing for dates that report zero market cap or have a market cap of less then 10% of the previous day's market cap. We then interpolate these observations from the last trading day immediately before to the first day immediately after this date. We also experiment with removing observations with open interest or an ETF market cap more than five studentized residuals from its centered one-year moving average, but this has a very limited impact on the results.

A.5. S&P 500 constituents and other US stock data

For the S&P 500 constituents, we obtain the list of index constituents, as well as stock returns, shares outstanding and turnover data, from CRSP, calculate analyst coverage from Institutional Brokers' Estimate System (I/B/E/S) data, and retrieve data on institutional ownership from the Thomson Financial 13f database. We replicate the S&P 500 index and the weights of each member using stock market capitalizations. We use these data from July 1962 onward as CRSP reports fewer than five hundred of the S&P's index members before this date. Further, we collect similar data of all US stocks not included in the S&P 500 from the same sources.

A.6. Nikkei 225 and TOPIX constituents

We collect the list of Nikkei 225 and TOPIX members from Compustat Global, which begins in 1985. As some constituents are merged or acquired and Compustat keeps only the most recent company identifier, we use Factset to cross-check the constituents in Compustat, identify stocks with this problem, and collect identifying information on such stocks before the takeover. Our sample of index constituents represent 99.4% of TOPIX capitalization and includes all Nikkei 225 stocks. The remaining 0.6% comes from very small stocks and we distribute them evenly across all available stocks.

A.7. Nikkei 225 par values

As Nikkei does not provide information on par value prior to 1998, we use the available information as starting point. We obtain information on par values from a recent constituent list on the exchange website (https://indexes.nikkei.co.jp/nkave/archives/file/nikkei_stock_average_weight_en.pdf), a weightings list from November 1, 2011 available in Datastream, the raw data used in Greenwood (2005) on Greenwood's website, and the weights on April 1, 1998, which is the earliest available date for data provided by Nikkei. By combining Factset with Compustat Global, we can determine the par values of all index constituents from 2000 onward (as this is available in Factset), which we supplement with constituents data for 1998 provided by Nikkei. For stocks that are a member of the Nikkei 225 in 1986 or later but exit the Nikkei 225 before 1998, we infer par values by minimizing the difference between the Nikkei 225 index and the aggregated price-weighted value of its constituents. We set the par value to 50 (as most stocks have a par value of 50) and change the par values to 500, 5,000, or 50,000 to minimize the daily tracking error between our reconstructed index and the actual index.

A.8. Control variables

For market volatility, we use realized (annualized) volatility over the last 21 days because it is available for all indexes (as implied volatility indexes are not available for many of them for a sufficiently long time). We use the difference between the three-month US LIBOR (as of 1984) or the eurodollar rate (between 1971 and 1984) and the three-month US T-bill interest rate (obtained from the Federal Reserve Board St. Louis and Bloomberg) to calculate the TED spread. We compute past market returns as the past month (i.e., 21 trading days) market return as Hameed et al. (2010) find that such a measure predicts serial dependence profits. Finally, for market volume, we use the log of index trading volume detrended by calculating the five-day average relative to a one-year backward moving average in the spirit of Campbell et al. (1993).

Appendix B. Serial dependence as a variance difference

Autocovariance over a certain time period can be replicated by the difference of two realized return variances that are evaluated over that same period T but differ in the frequency over which they are calculated, akin to variance difference statistics (see, for example, Campbell et al. (1997)). To see this, consider a short (e.g., one week) period of length T, divided into q intervals of equal length (e.g., five trading days), and a return from time 0 to T that equals the sum of the log returns $r_t, t = 1, \ldots, \frac{T}{q}$ with $\mathrm{E}(r_t) = \mu_t = 0$. The variance over the period T calculated over q intervals is $\mathrm{Var}(T, q) = \mathrm{Var}(r_1)+\mathrm{Var}(r_2) + \cdots + \mathrm{Var}(r_q)$, or

$$\mathrm{Var}(T, q) = \sum_{t=1}^{q} E(r_t^2) = \sum_{t=1}^{q} \mathrm{Var}(r_t). \tag{14}$$

However, when we calculate the return over the same period T, but over one instead of q intervals, the variance is

$$\begin{aligned}\mathrm{Var}(T, 1) &= E\left[\left(\sum_{t=1}^{q} r_t\right)^2\right] \\ &= \sum_{t=1}^{q} \mathrm{Var}(r_t) + \sum_{l=1}^{q-1} 2(q-l)\mathrm{Cov}(r_t, r_{t-l}). \end{aligned}\tag{15}$$

In Eq. (15), $\mathrm{Cov}(r_t, r_{t-l})$ is the autocovariance in returns between the current time unit $t = \frac{T}{q}$ and its lag $t-l$ assuming that, over short intervals, $\mathrm{Cov}(r_t, r_{t-l}) = \mathrm{Cov}(r_k, r_{k-l})\ \forall\, t \neq k$ (i.e., stationarity). Any serial correlation causes Eq. (14) to deviate from Eq. (15) because the autocovariance terms are nonzero and the difference between Eqs. (15) and (14) is simply a weighted sum of autocovariance terms from lag 1 up to lag $q-1$.

The autocovariance term can be isolated as the difference in returns between two investment strategies over period T (i.e., one that rebalances every interval q and one that buys and holds over the period T). First, after each of the q intervals, a rebalancing strategy adjusts its position to the initial position. As the price of the asset P changes over time, profits after interval t amount to $P_t/P_{t-1} - 1 = \exp(r_t) - 1$ and accumulate over period T to

$$\sum_{t=1}^{q} (\exp(r_t) - 1). \tag{16}$$

Approximating $\exp(r_t)$ with a second-order Taylor expansion around zero, $\exp(x) \approx 1 + x + \frac{1}{2}x^2$, we can rewrite the realized profits on the rebalancing strategy as

$$\sum_{t=1}^{q} \left(r_t + \frac{1}{2} r_t^2\right) = \sum_{t=1}^{q} r_t + \frac{1}{2}\mathrm{Var}(T, q), \tag{17}$$

where, over short periods, $\sum_{t=1}^{q} r_t^2 \approx \mathrm{Var}(T, q)$.

By similar arguments, the realized profit on a second, buy-and-hold strategy is

$$\begin{aligned}\exp\left(\sum_{t=1}^{q} r_t\right) - 1 &= \sum_{t=1}^{q} r_t + \frac{1}{2}\left(\sum_{t=1}^{q} r_t\right)^2 \\ &= \sum_{t=1}^{q} r_t + \frac{1}{2}\mathrm{Var}(T, 1) \end{aligned}\tag{18}$$

The difference between the buy-and-hold strategy and the rebalancing strategy then equals

$$\frac{1}{2}\mathrm{Var}(T, 1) - \frac{1}{2}\mathrm{Var}(T, q) = \sum_{l=1}^{q-1} (q-l)\mathrm{Cov}(r_t, r_{t-l}). \tag{19}$$

Thus, the variance difference in Eq. (1), an often used statistic to measure serial dependence, is equivalent to a simple trading strategy that replicates the return autocovariances above by taking $q-1$ positions as $r_t \sum_{l=l}^{q-1} (q-l) r_{t-l}, l = 1, \ldots, q-1$. For instance, to measure the serial dependence in one week of daily returns, $q = 5$ (a common horizon), one can take a position $4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4}$. Then, the daily return on our strategy is simply $r_t(4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4})$, which we scale into autocorrelations as

$$\mathrm{MAC}(5) = r_t(4r_{t-1} + 3r_{t-2} + 2r_{t-3} + 1r_{t-4})/(5 \cdot \sigma^2). \tag{20}$$

MAC(5) is equivalent to the (scaled) dollar difference between the buy-and-hold strategy and the rebalancing strategy, as $\sum_{l=1}^{q-1} (q-l) E\left[r_t, r_{t-k}\right] = \sum_{l=1}^{q-1} (q-l)\mathrm{Cov}(r_t, r_{t-k})$.

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