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Passive Institutional Ownership, R^2 Trends, and Price Informativeness

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Abstract

A distinctive trend in the capital markets over the past two decades is the rise in equity ownership of passive financial institutions. We propose that this rise has a negative effect on price informativeness. By not trading around firm-specific news, passive investors reduce the firm-specific component of total volatility and increase stock correlations. Consistent with this hypothesis, we find that the growth in passive institutional ownership is robustly associated with the growth in market model R^2s of individual stocks since the early 1990s. Additionally, we find

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a negative relation between passive ownership and earnings predictability, an informativeness proxy.

Keywords: comovement, volatility, informed trading, correlated trading, passive investing, institutional ownership, price informativeness

JEL Classifications: G14, G15, G18

1. Introduction

One of the most distinctive trends in capital markets over the past two decades is the rise in the equity ownership of passive financial institutions since the mid 1990s. The cause for this increase has been primarily attributed to changes in tax legislation that make defined contribution (i.e., 401k) plans attractive to retail investors and technological change that make rebalancing large indexed portfolios feasible at a very low cost.[1] Low transaction and monitoring costs have given passive investors the ability to charge lower fees and grow at the expense of actively managed funds. Figure 1 illustrates this spectacular rise. As of 1992, passive investors owned about 30% of the total market capitalization of the NYSE, Amex, and NASDAQ.[2] By December 2010, their ownership had risen to about 50% or 72% of all institutionally owned shares.

There is an ongoing debate among academics regarding the implications of this rise in capital market efficiency. Although retail investors clearly benefit from the diversification provided by certain passively managed portfolios (i.e., indexed funds), some scholars have started to question whether this benefit has not been overshadowed by passive investors' lack of fundamental-based trading that could increase stock return correlations and make prices less informative. Other studies contend that is not necessarily the case as passive investors have a positive effect on

[1] Portfolio rebalancing costs dropped dramatically with the introduction of online communications between buy-side managers and traders, which also facilitated basket trading or the execution of multiple orders at once. Just one year after the creation of the Hyper Text Markup Language (HTML) in 1991, the financial sector developed the Financial Information eXchange (FIX) Protocol. FIX is a standard language for transmitting messages from buy-side managers to traders, designed to match and execute institutional block orders through their own internal books (Securities and Exchange Commission [SEC], 1997). Basket trading intensified with the introduction of the new SEC regulations in 1997 (Order Handling Rules) and 1998 (Regulation ATS), which permitted electronic trading platforms to operate, the switch from tick-by-tick to decimal pricing in 2001, and the proliferation of hedge funds that provided the necessary computing resources to increase trading volumes (Northey, 2011).

[2] We identify passive institutional investors as those that meet the *quasi-indexer* definition in Bushee (1998, 2001) and Bushee and Noe (2000). Quasi-indexers are passive investors that use indexing or buy-and-hold strategies. Their portfolios are characterized as being well diversified and having low turnover. A list of quasi-indexers current to December 2010 was obtained from Brian Bushee's Institutional Investor classification website (http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html). All other financial institutions are classified as active (e.g., nonpassive).

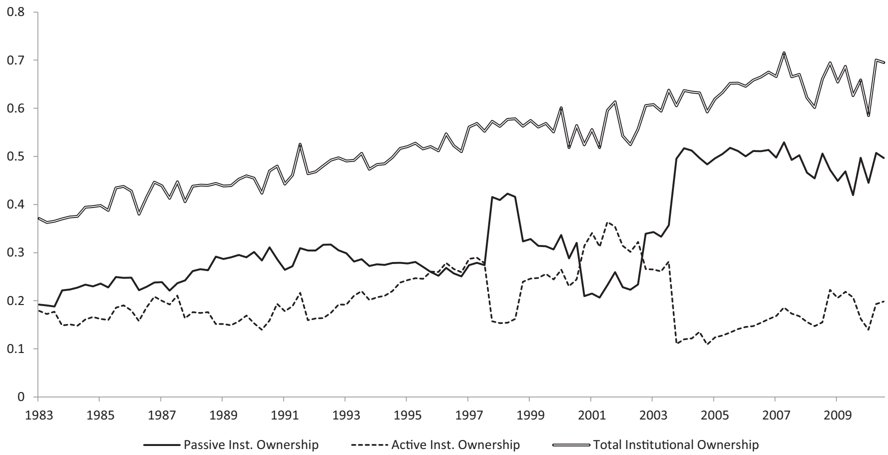

Figure 1

Stock ownership by institution type

Figure 1 shows the stock ownership of all financial institutions, passive financial institutions (quasi-indexers), and active financial institutions (transient and dedicated) from 1983 to 2010. Institutions are classified into passive or active categories using Brian Bushee's classification of financial institutions (available on his website). Institutional ownership is obtained from the SEC 13f reports.

the transparency and managerial disclosure of the firms whose stock they own, thereby reducing information asymmetries, improving liquidity, and keeping transaction costs down (e.g., Carleton, Nelson and Weisbach, 1998; Del Guercio and Hawkins, 1999; Boone and White, 2015; Appel, Gormley and Keim, 2016). Thus, even though passive investors cannot engage in arbitrage directly, the improved information environment they promote could allow others to effectively do so.

Despite this evidence, whether passive investing erodes market efficiency remains an empirical question. In their seminal paper, Grossman and Stiglitz (1980) suggest that the equilibrium number of informed investors needed for informational efficiency depends endogenously on structural factors that determine the size of the arbitrage profit. Structural factors that reduce information acquisition costs, such as transparency and information production, make detecting mispriced assets easier, but also reduce the size of the reward. Given that the risk-adjusted margins of passive investors currently exceed those of active investors, the reward needed to induce investors to acquire costly information might not be achievable. In addition, even if market inefficiencies were to reach a threshold that would induce active investing, one active manager's overperformance is often offset by another's underperformance causing the expected value of cheap passive funds to still dominate that of active management (Blitz, 2014).

Consistent with these caveats, several new studies suggest that the rise in passive investing could be eroding price informativeness, and that this erosion could be occurring across multiple markets. For instance, in a theoretical model, Bhattacharya and O'Hara (2016) predict that learning and feedback effects between exchange-traded funds (ETFs) and their underlying assets promote price instability and herding when the underlying asset is hard to trade. Examples of such hard-to-trade assets include high yield bonds, foreign equities, commodities, and other securities traded over-the-counter. Ehsani and Lien (2015) corroborate this prediction by finding a positive correlation between cumulative equity ETF trading volumes and the aggregate market model R^2, a proxy for stock market fragility (e.g., Kamara, Lou and Sadka, 2008). Brogaard, Ringgenberg and Sovich (2016) suggest that a reduction in the informativeness of commodity prices, caused by a rise in commodity index investing, is responsible for excess volatility in cash flows and stocks returns from firms heavily exposed to commodity prices as part of their operations. Similarly, Qin and Singal (2015) suggest a positive relation between index mutual fund ownership and the price informativeness of Standard & Poor's (S&P) 500 constituents, as measured by post-earnings announcement drift and deviations from the random walk. This paper is the closest to ours in aim and research design.

Passive investing is not fundamentals-based. Its trades are based on maintaining a benchmark index and passive institutions buy and sell stocks in lockstep. Therefore, in the absence of enough active trading, passive trading could lead to both increased stock return comovement and reduced price informativeness. Thus, the purpose of our research is twofold. First, we propose and determine that the rise in passive institutional ownership has contributed to the rise of U.S. stock return correlations over the past two decades. Our analyses find a positive association between a stock's passive institutional ownership growth and the trend of its market model R^2. This association dominates any effect ETF ownership has on stock correlations, contrary to some studies that investigate ETF holdings' impact on market efficiency (e.g., Ehsani and Lien, 2015; Israeli, Lee and Sridharan, 2015). In addition, we investigate whether passive institutional ownership either positively or negatively impacts stock price informativeness. To do so, we employ empirical methodology developed to determine a stock price's ability to reflect future earnings. Using this methodology, Jiambalvo, Rajgopal and Venkatachalam (2002) find that institutional ownership improves a stock's ability to reflect future earnings suggesting that institutional ownership has a positive effect on price informativeness. Although this is an important discovery, we find it to be incomplete as it only applies to stocks owned primarily by institutions following active investment strategies. For stocks owned primarily by passive institutions, we find a negative relation between stock ownership and a stock's ability to reflect future earnings. This suggests that passive institutional ownership actually erodes price informativeness.

Several studies have shown that correlations among stock returns, which declined consistently during the second half of the twentieth century (e.g., Campbell, Lettau, Malkiel and Xu, 2001), have been rising steadily since the early to mid

1990s and interpret this trend as a sign of increasing market fragility (e.g., Kamara, Lou and Sadka, 2008; Wurgler, 2010; Bradley and Litan, 2011; Sullivan and Xiong, 2012).[3] The empirical results we provide support these papers' conjecture and the hypothesis of a negative relation between passive institutional ownership and price informativeness. We identify passive institutional ownership as the equity ownership from institutional investors that are classified by Bushee (1998, 2001) and Bushee and Noe (2000) as "quasi-indexers," which consists of institutions whose investment strategy is very close to that of pure indexing. Consistent with our hypothesis, we find a positive relation between the linear trend coefficients of market model R^2s and changes in the passive equity ownership of individual stocks. Stocks that experienced the largest increases in passive ownership from 1993 to 2010 also showed the largest R^2 trend coefficients during this time. All else being equal, stocks in the highest quintile in passive ownership had an average R^2 trend of 7.12 basis points per month ($t = 17.75$), while those in the lowest quintile had an average R^2 trend of 5.42 basis points per month ($t = 11.19$).[4] A Wald test of parameter equality rejects the null of these trends being equal with an error probability of less than 1%. In addition, further testing reveals passive ownership to be economically and statistically more significantly related to the rise in stock correlations than other competing factors including correlated trading, correlated cash flows, and market frictions.

Our first result, that increases in passive institutional ownership is strongly associated with a rise in stock correlations over the past two decades, is not, in itself, a market efficiency test. This is because R^2 is a controversial statistic with studies in favor (e.g., Roll, 1988; Morck, Yeung and Yu, 2000; Wurgler, 2000; Durnev, Morck, Yeung and Zarowin, 2003; Durnev, Morck and Yeung, 2004) and against (e.g., Brandt, Brav, Graham and Kumar, 2010) its use as a price informativeness proxy. Therefore, to establish a direct link between passive ownership and price informativeness, we test the cross-sectional relation between passive ownership and earnings predictability. Following Jiambalvo, Rajgopal and Venkatachalam (2002), we use earnings predictability as a price informativeness proxy. Based on this measure, we are able to replicate this paper's main result, that the extent to which stock prices lead earnings is positively related to the extent of institutional ownership. However, we find that this result is only true among stocks owned primarily by institutions that are following active investment strategies. In contrast, increases in passive institutional ownership weaken the relation between a stock's price and its future earnings, a sign that passive institutional ownership is detrimental for price informativeness.

[3] In unreported analyses, we identify a structural break date in the average R^2 series of September 1992 using the Bai and Perron (1998, 2003) dynamic programming algorithm. The 95% confidence interval for the break ranges from July 1992 to October 1992. The results are available from the authors on request.

[4] After controlling for the effects of active institutional ownership, being part of multiple indices, cash flow comovement, firm size, analyst following, idiosyncratic noise, stock liquidity, and firm fixed effects on return comovement.

In summary, we find that a rise in passive institutional ownership since the early 1990s has contributed to higher return correlations and lower predictability of future earnings. We conclude that this rise could have reduced the investors' ability to extract fundamental-based information from price changes.

2. Sample and variable construction

2.1. Sample construction

Our period study is limited to the years from 1993 to 2010. The sample begins in 1993 as we determine a structural break in the average R^2 series of September 1992 and both average R^2 and average passive ownership increase since that year. The sample ends in 2010 due to data availability. The Bushee institutional ownership classification data ends in the year 2010. To be part of the sample, a stock must have data available to calculate returns, passive institutional ownership, and control variables. To avoid survivor bias in our results, we construct two samples: the full sample that includes all firms during the sample period and the survivor sample that excludes firms that were listed for only a portion of the sample period. The survivor sample contains 720 securities with 12,960 observations. The full sample includes 6,151 securities with 46,318 observations and 6,168 securities with 61,539 observations depending on the set of control variables used.

2.2. Variable descriptions

Tables 1 and 2 report descriptive statistics of the variables: market model R^2 (the dependent variable), passive institutional ownership (the independent variable), and proxies for four additional determinants of stock correlations: correlated trading, correlated cash flows, information production, and market frictions. We winsorize each variable's distribution at the 0.5% and 99.5% levels to limit the effect of outliers.

2.2.1. Market model R^2

Market Model R^2 is the coefficient of determination of the regression of daily individual stock returns on value-weighted market and industry returns over the previous calendar year. To control for the effects from thinly traded stocks, we only include stocks that traded for at least 250 trading days over the prior 12 months. Average (median) annual R^2 values are 0.17 (0.09) for the full sample and 0.22 (0.16) for the survivor sample. The standard deviation of the annual R^2s is 0.18 (0.20) for the full (survivor) sample and its range fluctuates between near 0 and 0.85.

Table 1

Descriptive statistics for the pooled samples

This table presents the descriptive statistics of the market model R^2 and its determinants. The samples consist of annual observations from 1993 to 2010. We construct two samples, the *Full Sample* and the *Survivor Sample*. The *Full Sample* includes all common and ordinary stocks in CRSP with available comovement and controls. The *Survivor Sample* only includes the common and ordinary stocks with available returns during the entire 1993–2010 period. R^2 is the market model R^2 of each individual stock over the past 12 months, using daily data as of December 31st of each year. We only include stocks listed for a minimum of 250 trading days over the year. We use the CRSP value-weighted index as the market index. *Passive Institutional Ownership* is the percentage of common and ordinary shares held by quasi-indexers in the second quarter of each year (e.g., Bushee and Noe, 2000; Bushee, 2001). *Active Institutional Ownership* is the percentage of common and ordinary shares held by financial institutions other than quasi-indexers. *ETF Ownership* is the percentage of common and ordinary shares held by Exchange Traded Funds. These data are available from 2004 to 2010 only. *Number of Index Memberships* is the number of Standard and Poor's indexes that a stock belongs to. *Sales per Share* R^2 is the coefficient of the determination of quarterly unanticipated shocks to sales per share regressed on market and industry sales over the past 20 quarters following Irvine and Pontiff (2009). Sales per share information comes from Standard & Poor's Compustat. *Market Capitalization* is the market value of equity in millions of dollars at the end of the previous June. *Number of Analysts* is the number of earnings per share forecasts from I/B/E/S. *Noise* is the absolute value of the autocorrelation coefficient of market model residuals. All variables are winsorized at the 0.5% and 99.5% levels.

	σ		Mean		Min		q1		Median		q3		Max
	Full	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full & surv*
R^2	0.18	0.20	0.17	0.22	0.00		0.02	0.04	0.09	0.16	0.27	0.36	0.85
Passive Inst. Ownership	0.19	0.18	0.29	0.35	0.00		0.12	0.22	0.29	0.37	0.44	0.48	0.92
ETF Ownership	0.02	0.02	0.01	0.02	0.00		0.00		0.00		0.02	0.03	0.13
Market Capitalization ($mm)	11,618	17,691	3,068	6,279	2.19	2.54	62.36	160.0	293.29	865.2	1,420.95	3,692.8	162,714.4
Correlated trading proxy													
Num. of Index Memberships	6.01	5.94	5.04	7.40	0.00		0.00		0.00	11	12		17
Correlated cash flows proxies													
Sales/Share R^2	0.16	0.18	0.15	0.17	0.00		0.04		0.10	0.11	0.22	0.25	0.93
Information production proxy													
Number of Analysts	7.60	8.74	5.96	7.89	0		0		3	5	9	13	40
Active Inst. Ownership	0.14	0.12	0.17	0.17	0.00		0.05	0.08	0.14	0.16	0.26	0.25	0.71
Market friction proxies													
Noise	0.11	0.10	0.12	0.11	0.00		0.04		0.09	0.08	0.17	0.14	0.54
Turnover	4.12	4.85	1.64	4.17	0.00		0.25	1.12	0.67	2.61	1.66	5.27	49.15
Volume ($mm)	1,979	2,606	626	1,020	0.00		8.52	17.7	65.35	154.2	379	792.3	3,600
Inv. Amihud ($\times 10^{-7}$)	500	742.8	121	231.6	0.00		0.16	0.80	3.31	16.94	44.3	129.5	9,096
Number of trading days	31.38	26.11	240.20	244.03	29		247	250	252		252		254

Table 2

Frequency counts for index and style investing indicators

This table reports the annual number of additions and deletions from Standard and Poor's large cap, mid cap, and small cap indexes, as well as the category of a low priced stock (defined as having a price of less than $5).

Year	Number of additions								Number of deletions							
	Large cap		Mid cap		Small cap		Low-priced		Large cap		Mid cap		Small cap		Low-priced	
	Full	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*	*Full*	*Surv*
1993	2	1	7	3	0	0	44	6	0	0	2	1	0	0	82	23
1994	4	1	6	3	0	0	49	8	2	0	3	1	0	0	90	12
1995	14	7	8	4	295	75	88	10	5	3	5	1	0	0	68	13
1996	11	8	12	1	23	9	62	5	6	1	13	7	3	0	123	20
1997	8	2	12	3	26	10	70	8	5	2	12	6	8	2	58	14
1998	22	9	15	4	47	15	53	4	6	4	16	4	8	0	81	21
1999	17	7	21	3	25	6	165	27	7	1	24	9	17	4	33	4
2000	23	7	21	6	43	8	99	20	1	1	24	10	16	2	109	11
2001	22	6	38	15	58	13	167	20	6	5	27	7	25	4	55	9
2002	13	6	26	7	27	7	115	11	13	5	31	9	38	11	98	19
2003	6	1	18	6	24	5	166	16	4	2	20	7	24	4	39	5
2004	8	2	21	5	23	4	20	2	2	1	20	4	29	7	284	37
2005	31	4	13	6	21	6	91	6	2	1	15	4	22	4	72	8
2006	19	3	22	4	38	3	49	4	8	5	6	1	11	2	79	8
2007	13	5	22	8	43	3	59	4	6	0	14	4	13	4	66	12
2008	20	6	26	8	37	3	118	8	6	2	18	6	10	3	26	4
2009	28	5	41	9	50	13	363	60	8	2	14	7	16	5	6	0
2010	15	4	26	9	26	4	91	11	18	7	42	11	41	7	122	31
Total	276	84	355	104	806	184	1,869	230	105	42	306	99	281	59	1,491	251

2.2.2. *Passive institutional ownership*

We define passive institutional ownership as the percent of common and ordinary shares owned by institutional portfolios that use passive investment strategies. Quarterly institutional ownership data is from the Thomson Financial 13(f) database.[5] We identify passive financial institutions by their manager's behavior following Bushee (1998, 2001) and Bushee and Noe (2000). Bushee classifies financial institutions into

[5] Institutional holdings data is public information. Institutional investors operating in the United States with portfolios of $100 million or more are required to file 13(f) reports with the SEC within 45 days of the end of each calendar quarter. The reports contain information on all equity positions greater than 10,000 shares or $200,000 in market value. The stock holdings in the 13(f) reports constitute the dominant majority of true institutional holdings. According to Sias, Starks and Titman (2006), the total market value of the equity holdings of institutions filing 13(f) reports (and thus included in the database) accounts for about 90% of the Conference Board estimate of total equity holdings by institutional investors.

quasi-indexers, transient, and dedicated.[6] A list of quasi-indexer, transient, and dedicated financial institutions current to December 2010 is available at Brian Bushee's Institutional Investor classification website. Portfolios of quasi-indexers have low turnovers and diversified holdings consistent with a passive buy-and-hold strategy of investing in a broad set of firms. Alternatively, transient and dedicated institutions follow more active investment styles. Bushee (2001, p. 214) describes these institutional investors in the following manner: "Transient institutions are characterized as having high portfolio turnover and highly diversified portfolio holdings. These traits reflect the fact that transient institutions tend to be short-term-focused investors whose interest in the firm's stock is based on the likelihood of short-term trading profits. Dedicated institutions are characterized by large average investments in portfolio firms and extremely low turnover, consistent with a 'relationship investing' role and a commitment to provide long-term patient capital." Dedicated institutions have concentrated holdings indicating a more active style of management than quasi-indexers.

Our proxy for U.S. passive institutional ownership is equal to the common and ordinary equity shares owned by quasi-indexers as a percent of the total common and ordinary equity shares outstanding for all firms in the CRSP database. We treat all institutions not classified as quasi-indexers by Bushee (1998, 2001) as following active investment styles, either as fundamental-based or speculative traders. Average and median passive institutional ownership for the full sample is 29%, while average (median) passive institutional ownership for the survivor sample is 35% (37%). The range of passive ownership varies widely from 0 to 92%, providing ample opportunity to examine how passive institutional ownership influences the market model R^2.

2.2.3. Market capitalization

Market capitalization is a proxy for several determinants of comovement. Traditionally, market capitalization has been used as a proxy for information supply. Crawford, Roulstone and So (2012, p. 1536) explain that market capitalization proxies for "various dimensions of the firm's information environment, including media exposure and the overall level of investor interest." At the same time, the size of the

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[6] The classification methodology consists of performing a factor analysis on institutional holdings and a variety of characteristics (e.g., Bushee, 1998, p. 325). A *k*-means cluster analysis is then executed on the factor scores to group institutions into their appropriate category. While this method requires some initial cluster seeds, the large number of observations makes the cluster formation insensitive to both the initial seeds and to the order in which the observations are clustered (Hair, Black, Babin, Anderson and Tatham, 2006). This classification has proven to be robust in the literature and is used in scores of studies across a broad range of disciplines including accounting (e.g., Collins, Collins, Gong and Hribar, 2003; Ke and Petroni, 2004; Ke and Ramalingegowda, 2005; Ramalingegowda and Yu, 2012; Bentley, Omer and Sharp, 2013), finance (e.g., Gong, Louis and Sun, 2008; Cai, Garner and Walking, 2009; Field and Lowry, 2009; Joe, Louis and Robinson, 2009; Yan and Zhang, 2009; Burns, Kedia and Lipson, 2010; Cremers and Pareek, 2015; Yüksel, 2015), management (e.g., Connelly, Tihanyi, Certo and Hitt, 2010; Eccles, Ioannou and Serafeim, 2014), and marketing (e.g., Luo, Zhang, Zhang and Aspara, 2014).

firm's equity is also related to market frictions and correlated trading, as stocks from large firms tend to be more liquid and belong to multiple indexes that are owned by ETFs. The average (median) firm in the full sample has capitalization of $3,068 ($293.29) million, while the average firm in the survivor sample is about twice that size, with average (median) capitalization of $6,279 ($865.2) million. The difference between means and medians in both samples reveals the presence of some very large firms that skew the distribution. Market capitalization in our sample varies widely from $2.19 ($2.54) million to $162.7 billion in the full (survivor) sample.

2.2.4. Correlated trading

There are at least three different mechanisms through which correlated trades can be generated by passive investors, namely open-end index funds and ETFs. First, correlated trades can arise when open-end index fund managers buy and sell shares of all of the stocks in their portfolios to accommodate net fund flows (e.g., Wurgler, 2010; Bradley and Littan, 2011; Sullivan and Xiong, 2012). Index fund trading should not cause excess market-wide comovement unless similar trading is occurring with stocks outside of the benchmark index. However, as the number of publicly available indexes and index funds increases, many stocks no longer belong to just one index, but are part of multiple indexes. The larger the number of indexes to which a stock belongs, the greater the likelihood that a stock will be bought or sold alongside many other stocks in the market and the higher the possibility that its returns will comove with the returns of other stocks.

In addition, correlated trading arises through the "in kind" creation/redemption process of ETFs (e.g., Da and Shive, 2012; Staer, 2012; Broman, 2015). This mechanism gives certain large institutional investors called Authorized Participants (APs) the right to buy or redeem ETF shares in bundles directly from the ETF sponsor. In this way, APs can arbitrage mispricing between ETF shares and their underlying portfolios. As with open-end funds, the synchronized purchase or sale of securities in a single ETF should not have an effect on comovement at the market level. However, Broman (2015) finds a common component in equity ETF mispricing that makes synchronized ETF creations and redemptions likely. Therefore, with more shares owned by ETFs, there is a stronger possibility of synchronized in kind redemptions/creations in multiple ETFs and an increased chance for correlated trading.

Also, correlated trading can arise due to style and habitat investing. Style and habitat investing occurs when investors focus their attention on certain assets while neglecting others. Style investing refers to limiting a portfolio to stocks with common characteristics including industry affiliation, size, price, market-to-book, or momentum (e.g., Barberis and Shleifer, 2003; Barberis, Shleifer and Wurgler, 2005). Alternatively, habitat investing refers to limiting a portfolio to a publicly available index, such as the Dow Jones Industrial Average or the S&P 500, or stocks within a certain price range (e.g., Kumar, Page and Spalt, 2013). When a stock is added (dropped) to (from) an index or asset class, comovement with other index or asset class constituents increases (declines), while comovement with the market declines (increases) (e.g., Vijh, 1994; Lynch and Mendenhall, 1997; Kaul, Mehrotra and Morck, 2000; Wurgler and Zhuravskaya, 2002; Barberis, Shleifer and Wurgler, 2005; Greenwood and Sosner, 2007; Greenwood, 2008; Claessens and Yafeh, 2013).

Throughout our empirical tests, we control for correlated trading using three proxies:

(1) *Number of Index Memberships*: The *Number of Index Memberships* is equal to the number of indexes in the S&P family that a stock belongs to in a given year. The reasoning underlying our use of this variable is that a larger set of index memberships potentially results in a greater number of funds holding positions in a given stock and a greater aggregate trading volume that would be evident in increased comovement. However, there are two possible and opposite ways in which this variable could be related to comovement. First, when a stock belongs to multiple broadly based indexes, the relationship between *Number of Index Memberships* and R^2 would likely be positive if correlated purchases and the redemption of index fund shares involve a large cross-section of stocks. Alternatively, when a stock belongs to more style-based indexes, the relation between *Number of Index Memberships* and R^2 could be negative when trading is concentrated in and correlated with stocks of the same style, but not with all of the other stocks in the market. However, we believe that the likelihood of this second scenario being dominant is low due to the preponderance of broadly based indexes. Thus, expect any observed relationship between *Number of Index Memberships* and R^2 to be positive.

(2) *ETF Ownership*: *ETF Ownership* is a proxy for correlated trading produced by the in kind creation/redemption process of ETFs and is equal to the proportion of common and ordinary stocks owned by ETFs. We obtain ETF ownership data from the CRSP Mutual Fund Database. ETF holdings do not appear in this data set until 2003, presumably because they were negligible prior to this year. We expect that stocks more heavily owned by ETFs will be subject to more correlated trading due to more in kind creation/redemption of ETF shares. Therefore, we expect a positive relation between *ETF Ownership* and R^2.

(3) *Index and Investment Style Addition/Deletion Indicators*: We use an indicator that denotes additions into and deletions from the set of “low priced” stocks. This indicator is a proxy for correlated trading arising from style investing. Additions (deletions) into low priced stock indicators take a value of 1 when the average price over the past 23 months declines below (climbs above) $10 per share. The use of this indicator arises from Green and Hwang’s (2009) finding that stocks with similar prices tend to comove more than with stocks that have very different prices. In addition, we use a set of indicators that denote additions into and deletions from popular indexes. These variables

proxy for correlated trading arising from habitat effects. Our indicators take values of 1 when stocks are added into or deleted from any large cap, mid cap, or small cap S&P indexes during the year.[7] Based on the habitat and style investing literature, we expect that stocks added to an index and the low priced stock category will start to comove more strongly with other stocks in the same index or asset class and less with the rest of the market. Thus, we expect a negative (positive) relation between addition (deletions) indicators and R^2.[8]

Tables 1 and 2 report the descriptive statistics for the correlated trading proxies used in our analysis. Table 1 presents the summary statistics for the continuous variables, while Table 2 reports frequency counts for the indicators. The average stock in our full (survivor) sample is part of about five (eight) indexes. In contrast, the median stock in our full sample belongs to no index, while the median stock of our survivor sample belongs to 11 indexes. The large discrepancy between means and medians in the full sample reveals skewness. Over half of the firms in the full sample do not belong to any index. In contrast, the firm that marks the 75th percentile of the sample belongs to 12 indexes. In the case of the survivor sample, the difference between the mean and the median is not as large. This suggests that most of the stocks that belong to multiple indexes have been listed for quite some time and that multiple index memberships do not extend to the entire market.

Table 2 reports the number of additions into and deletions from large cap, mid cap and small cap S&P indexes and the low priced stock category. The number of additions and deletions involve a small number of firms in our samples. In total, there are 5,489 additions and deletions among the stocks in the full sample representing 11.85% of all of the firms. From these, 2,129 belong to indexes and the remaining 3,360 are low priced stocks. Because the number of publicly available indexes has increased, the number of additions into the indexes (1,437 additions involving 3.01% of firms) has exceeded the number of deletions (692 deletions involving 1.49% of firms). Alternatively, the number of additions and deletions into the low priced stock category are almost matched (1,869 additions vs. 1,491 deletions). Frequency counts for the survivor sample reveal similar patterns than those described for the full sample. Although it has been widely determined that habitat and style investing can influence comovement, only deletions from habitats or investment styles would be consistent with a positive comovement trend. Table 2 shows that the number of deletions in our sample is very small.

[7] S&P index constituents are available from Compustat. We recognize that there are many indices other than those of S&P. However, membership in a characteristic S&P index will be highly correlated with membership in the same characteristic index sponsored by a different entity.

[8] This expectation is consistent with the evidence found by Barberis, Shleifer and Wurgler (2005), where stocks that are added to (deleted from) the S&P 500 Index subsequently comove more (less) with other S&P 500 stocks and less (more) with the market.

2.2.5. Correlated cash flows

Standard finance theory establishes a one-to-one relation between equity prices and discounted cash flows in the absence of market frictions. Therefore, we expect a positive association between cash flow R^2 and market model R^2. We measure cash flow R^2 as the coefficient of determination from the regression of unanticipated cash flow shocks on unanticipated shocks to the market and industry cash flow indexes. The cash flow proxies used are quarterly earnings, free cash flow, and sales per share. We use cash flow shocks to control for the persistency of cash flow levels. We measure these shocks as the residuals from the following pooled regression:

$$E_{it} - E_{it-4} = \propto + \beta_1 (E_{it-1} - E_{it-5}) + \beta_2 (E_{it-2} - E_{it-6}) + \beta_{13} (E_{it-3} - E_{it-7}) + e_{it}, \quad (1)$$

where E_{it} represents cash flow per share of firm i in quarter t. The residual e_{it} represents unexpected innovations to cash flow per share. The dependent variable is the difference between cash flow per share in quarter t and cash flow per share in quarter $t-4$ a year earlier. Cash flow shocks are standardized by dividing them by price at the end of the previous quarter. We create quarterly market and industry indexes of cash flow shock to price ratios by computing weighted average cash flow shocks for the market and Fama and French's (1997) 48 industries. Finally, in the fourth quarter of each year, we regress quarterly individual cash flow shocks on contemporaneous shocks to market and industry indexes over the past five years.

We estimate unanticipated shocks to cash flow per share on the fourth quarter of each year following Irvine and Pontiff (2009). For brevity, from these three proxies, we only report the results for sales per share. Table 3 reports an average (median) sales per share comovement of 0.15 (0.10) for the full sample with a range of variation between 0.00 and 0.93. Summary cash flow comovement statistics for the survivor sample are not very different. These values are similar to those obtained for the average and median return comovement (average of 0.17, median of 0.09, and range between 0 and 0.85).

2.2.6. Information production

Piotroski and Roulstone (2004) examine how economic agents can have an effect on comovement by incorporating different types of information into stock prices. They find that corporate insiders and institutional investors (those that follow active trading strategies) have a negative effect on comovement by incorporating firm-specific information. Alternatively, other studies demonstrate that analyst coverage has a positive effect on comovement that results from reducing uncertainty while interpreting firm-specific information (e.g., Schutte and Unlu, 2009) and providing market and industry information (e.g., Crawford, Roulstone and So, 2012).

As with passive institutional ownership, we identify active financial institutions following Brian Bushee's Institutional Investor Classification. Active institutional

Table 3

Pairwise Pearson's correlations for the pooled samples

This table presents the correlation coefficients for the determinants of the change in comovement. The samples consist of annual observations of stock return comovement and their determinants from 1993 to 2010. This table also reports the pairwise Pearson's correlations for two samples, the *Full Sample* and the *Survivor Sample*. The *Full Sample* consists of all common and ordinary stocks in the CRSP database with available return comovement and control variables. The *Survivor Sample*, whose correlations are in parentheses, consists only of the common and ordinary stocks in the CRSP database with return information available during the entire 1993–2010 period. Variable definitions are the same as in Table 1. All variables in the sample are winsorized at the 0.5% and 99.5% levels.

	Ln(R^2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(2) Ln(Passive inst. ownership)	0.62											
	(0.60)											
(3) Ln(Active inst. own.)	0.50	0.58										
	(0.45)	(0.49)										
(4) Ln(ETF Ownership)	0.40	0.39	0.25									
	(0.31)	(0.32)	(0.19)									
(5) Ln(# of index memberships)	0.57	0.64	0.41	0.29								
	(0.64)	(0.65)	(0.40)	(0.20)								
(6) Ln(Sales per share comov.)	0.09	0.07	0.03	0.08	0.07							
	(0.12)	(0.08)	(0.01)	(0.10)	(0.09)							
(7) Ln(Market Capitalization)	0.74	0.67	0.51	0.21	0.70	0.10						
	(0.73)	(0.61)	(0.42)	(0.08)	(0.74)	(0.13)						
(8) Ln(Number of Analysts)	0.59	0.61	0.50	0.30	0.59	0.08	0.72					
	(0.55)	(0.55)	(0.42)	(0.18)	(0.61)	(0.09)	(0.70)					
(9) Ln(Noise)	−0.49	−0.38	−0.37	−0.17	−0.33	−0.05	−0.46	−0.37				
	(−0.46)	(−0.34)	(−0.31)	(−0.14)	(−0.35)	(−0.06)	(−0.41)	(−0.31)				
(10) Ln(Share Volume)	0.71	0.62	0.56	0.31	0.60	0.09	0.79	0.68	−0.54			
	(0.71)	(0.61)	(0.51)	(0.20)	(0.68)	(0.12)	(0.81)	(0.70)	(−0.45)			
(11) Ln(Turnover)	0.62	0.56	0.62	0.42	0.46	0.06	0.53	0.55	−0.58	0.78		
	(0.63)	(0.56)	(0.49)	(0.42)	(0.51)	(0.10)	(0.49)	(0.51)	(−0.39)	(0.73)		
(12) Ln(Inverse Amihud)	0.79	0.73	0.60	0.28	0.71	0.09	0.95	0.74	−0.56	0.85	0.39	
	(0.79)	(0.68)	(0.51)	(0.17)	(0.77)	(0.13)	(0.95)	(0.72)	(−0.50)	(0.87)	(0.67)	
(13) Ln(Number of trading days)	0.41	0.34	0.30	0.18	0.27	0.04	0.41	0.34	−0.44	0.72	0.27	0.48
	(0.41)	(0.35)	(0.29)	(0.14)	(0.33)	(0.06)	(0.37)	(0.31)	(−0.35)	(0.66)	(0.40)	(0.45)

ownership is the common and ordinary equity shares owned by transient and dedicated institutions as a percent of the total common and ordinary equity shares in CRSP. In general, active ownership is smaller than passive ownership in both the full and survivor samples. Average active ownership for the full and survivor samples is 17% (14% and 16% for the medians, respectively) and takes values between 0 and 71%.

Following Chang, Dasgupta and Hilary (2006), analyst coverage is the maximum number of analysts to issue annual earnings forecasts over the past 12 months. Analyst forecast data comes from *I/B/E/S*. Following standard practice, we assume that firms not in *I/B/E/S* have no analyst following. Mean and median analyst coverage is 5.96 and 3 for the full sample and 7.89 and 5 for the survivor sample. The number of analysts covering a stock ranges from 0 to 40.

2.2.7. Market frictions (Noise)

Formally defined, market frictions are those market conditions that violate the capital-asset pricing model's perfect market assumptions. We use a parsimonious measure called *Noise* to capture the impact of information and liquidity-based frictions on price formation. This variable, constructed in the spirit of Boehmer and Kelley (2009), measures the extent that stock prices deviate from a random walk. We define *Noise* as the autocorrelation coefficient of daily market model residuals. We calculate this variable in annual frequencies using daily returns from July through the following June. To obtain our measure, we regress the returns of individual stocks on day t with market returns on day t, extract the model estimation residuals, and calculate the correlation between residuals on day t and residuals on day $t - 1$. Given that deviations from a random walk can produce either positive or negative autocorrelations, we define *Noise* as the absolute value of the autocorrelation coefficient. Thus, a *Noise* of 0 indicates that unexplained returns follow a random walk, while large values show that unexplained returns depart substantially from a random walk. Average *Noise* is 0.12 (median of 0.09) and it ranges from 0 to 0.54.

2.2.8. Market frictions (liquidity)

In addition to *Noise*, we include liquidity variables to proxy for market frictions. Using standard methods, we compute the following four liquidity variables: stock turnover, dollar volume, the inverse of the Amihud (2002) illiquidity measure, and the number of days traded during the past 12 months. The mean turnover (1.64) is significantly higher than its median (0.67). Similar discrepancies are evident between the means and medians in dollar volume (average of \$626 million and median of \$65.35 million) and the inverse Amihud measure (average of 44.10×10^{-7} and median of 0.30×10^{-7}). This suggests a strong tilt in the sample toward liquid stocks. Despite this tilt, there is still enough variation in the data to differentiate between liquid and illiquid stocks. The number of days of trading in a year ranges

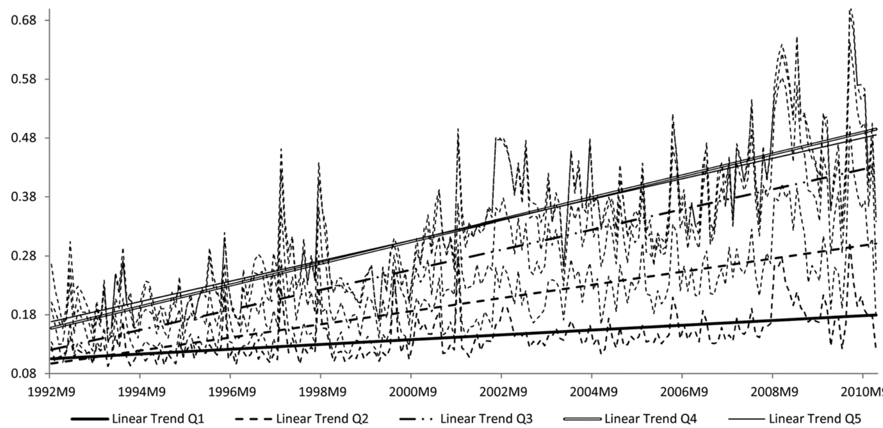

Figure 2

Equally weighted average market model R^2 for stocks sorted on passive institutional ownership, September 1992–December 2010

Figure 2 displays the equally weighted average R^2 statistic grouped by passive institutional ownership. We compute monthly equally weighted average R^2 statistics from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns and then group these individual R^2s by the average ownership of quasi-indexers in the previous year. Quasi-indexers are identified using Brian Bushee's classification of financial institutions, available on his website, and institutional ownership is obtained from the SEC 13f reports. We smooth each series using a 12-month moving average.

widely from 29 to 254, but the average and the median number of days traded are quite high (mean of 240.20 and median of 252) relative to the standard deviation (31.38 days). This implies that the vast majority of the sample stocks are actively traded.

3. Influence of passive institutional ownership on firm-level R^2 trends

Our hypothesis states that passive institutional ownership reduces the proportion of trades motivated by firm-specific information. Based on this hypothesis, we propose that increases in passive institutional ownership explain the positive trend in average R^2 since the early 1990s.

To test this hypothesis, we examine the R^2 trends of individual stocks while controlling for changes in their determinants other than passive institutional ownership. We calculate the average trend coefficients for securities in the survivor sample sorted on passive institutional ownership growth from 1993 to 2010. The results from these tests are presented in Figure 2 and Table 4.

Table 4

Linear trend of R^2 of individual stocks grouped by increases of passive institutional ownership: 1993–2010

This table presents pooled generalized method of moments regression coefficients of individual stock comovement on time and control variables for observations in the *Survivor Sample*. We use Newey-West errors with one lag to account for serial correlation in the residuals. *t*-Statistics are presented in parentheses. The dependent variable is the natural logarithm of the market model R^2 of individual stock returns. *Year* is a count variable that takes a value of 1 in 1993 and increases by 1 in subsequent years. *Q1*, *Q2*, *Q3*, *Q4*, and *Q5* denote the quintile a firm belongs to in terms of change in passive institutional ownership from 1993 to 2010. We include the following control variables: the natural logarithm of active institutional ownership, the number of Standard and Poor's' index memberships, sales comovement, market capitalization, analyst following, idiosyncratic noise, trading volume, share turnover, the inverse of Amihud's (2002) measure, the number of days traded in the year, and firm dummies (i.e., firm fixed effects). Variable definitions are the same as in Table 1. All variables in the sample are winsorized at the 0.5% and 99.5% levels.

	(1)	(2)	(3)	(4)
Intercept	−245.515		−116.73	
	(−38.21)		(−25.58)	
Year	0.1216***		0.0526***	
	(37.90)		(23.16)	
Q1*year		0.0880***		0.0542***
		(10.19)		(11.19)
Q2*year		0.0937***		0.0388***
		(12.22)		(9.78)
Q3*year		0.1180***		0.0495***
		(18.38)		(12.33)
Q4*year		0.1313***		0.0579***
		(21.16)		(14.14)
Q5*year		0.1769***		0.0712***
		(33.59)		(17.75)
Change in passive institutional ownership quintile dummies	No	Yes	No	Yes
Firm dummies	Yes	Yes	Yes	Yes
Controls (9)	No	No	Yes	Yes
[Wald statistic, *p*-value, null: $\beta_{Q1*year}=\beta_{Q2*year}=\beta_{Q3*year}=\beta_{Q4*year}\ \beta_{Q5*year}$]		[2,196.80; <0.0001]		[725.43; <0.0001]
[Wald statistic, *p*-value, null: $\beta_{Q1*year}=\beta_{Q5*year}$]		[253.65; <0.0001]		[204.72; <0.0001]
Number of observations	12,960	12,960	12,960	12,960
Adjusted R^2	0.1497	0.1971	0.6794	0.6826

*** indicates statistical significance at the 1% level.

3.1. Cross-correlations

Table 3 presents pairwise Pearson's correlations for all of the variables in the full and survivor samples. We winsorize each variable's distribution at the 0.5% and 99.5% levels and take natural logs to reduce the influence of outliers. Additionally, taking the natural log of the variables allows the estimated coefficients to be interpreted as elasticities. The correlation coefficient of 0.62 (0.60) between R^2 and *Passive Institutional Ownership* for the *Full (Survivor) Sample* is consistent with our hypothesis. We also find strong correlations between R^2s and other variables including *Active Institutional Ownership* (0.50), *ETF Ownership* (0.40), *Number of Index Memberships* (0.57), *Firm Size* (0.74), *Analyst Coverage* (0.59), *Share Volume* (0.71), *Turnover* (0.62), and the *Inverse Amihud* measure (0.79). There is also a strong negative correlation between R^2 and *Noise* (−0.49). With the exception of *Active Institutional Ownership*, that according to theory should be negative, the sign of all of the coefficients conform to the prior literature. As expected, we find positive correlations between R^2 and correlated trading and R^2 and *Analyst Coverage*, and negative correlations between R^2 and market friction proxies.

Table 3 also reveals some very strong correlations between *Passive Institutional Ownership*, our independent variable, and controls that include *Active Institutional Ownership* (0.58), *Number of Index Memberships* (0.64), *Firm Size* (0.67), *Analyst Coverage* (0.61), *Share Volume* (0.62), *Turnover* (0.56), and the *Inverse Amihud* measure (0.73). This suggests dependence on common omitted factors that include financial deregulation and institutional change, the range of financial products, and risk sharing opportunities that have started to emerge since the 1980s (e.g., Rajan and Zingales, 2003; Shiller, 2003).

In general, R^2 is highly correlated with all of the treatment variables and controls except for *Cash Flow Comovement*. Average correlations between *Cash Flow Comovement* and all of the other variables are also very low.

Although these coefficients largely support our hypothesis, it is possible that their magnitude could be overstated due to common omitted factors. In addition, pairwise correlations support multiple potential explanations for the positive R^2 trend. To better understand which of these factor(s) better explains R^2's trend, we examine the effect of passive institutional ownership on R^2's trend in a multivariate setting.

3.2. R^2 trends and changes in passive institutional ownership

We calculate the change in passive institutional ownership from 1993 to 2010 on each security in our survivor sample. We then sort securities into quintiles according to this change. On average, passive institutional ownership grew by 14.4% from 1993 to 2010. Stocks in the top passive institutional ownership growth quintile increased by an average 37%, while institutional ownership in the lowest quintile declined by an average 5.7%. Figure 2 tracks the evolution of equally weighted average R^2 for each of these groups. It is evident from looking at this figure that stocks in the top two quintiles have experienced much faster increases in their R^2s than the rest of stocks in the sample, and that the average R^2 slope becomes steeper as we move across quintiles from low to high.

We take a closer look at R^2 trends across quintiles of passive institutional ownership growth using pooled regressions. Table 4 presents the coefficients from pooled general method of moments regressions of the natural logarithm of individual R^2s on a time dummy, firm dummies (i.e., firm fixed effects), and controls. To account for the effect of serial correlation on the standard errors, we use Newey-West errors with one lag. We fit four different model specifications. In Model (1), individual R^2s are regressed on year (t) and firm dummies to account for firm-specific factors that could have resulted in higher market correlations. For example, increases in market share could have turned a firm into a bellwether firm that investors use to price other stocks in the same industry (e.g., Hou, 2007). The average trend for securities in the survivor sample is 12.2 bps per month ($t = 37.90$).

In Model (2), individual R^2's are regressed on dummy variables that denote quintiles of the change in passive institutional ownership growth from 1993 to 2010, interaction terms between these dummies and *Year*, and firm dummies. The interaction terms for stocks in the lowest quintile have an average trend of 8.8 bps per month ($t = 10.19$). This coefficient increases monotonically as we move across quintiles from lowest to highest and reaches 17.7 bps per month ($t = 33.59$) in the top quintile. In addition, two Wald tests fail to reject the null that coefficients from all of the interaction terms are statistically equal (Wald statistic of 2,196.8 with a p-value of less than 0.0001) and that the coefficient on the interaction term of the top passive ownership quintile is higher than the coefficient on the interaction term of the lowest passive ownership quintile (Wald statistic of 253.65, p-value of less than 0.0001). The increase in trend coefficients across the *Passive Institutional Ownership* growth quintiles in Model (2) and the accompanying test of difference in trend coefficients fully supports our hypothesis.

In Models (3) and (4), we repeat the estimation from Models (1) and (2) while controlling for firm-specific factors and other determinants of R^2's growth including active institutional ownership, the number of S&P index memberships, sales comovement, market capitalization, the number of analysts following the stock, firm-specific noise, trading volume, firm turnover, the inverse of Amihud's illiquidity measure, and the number of days the stock traded during the year. We take the natural logarithm of all of these variables before fitting them into the model equation. The coefficient of interest in Model (3) is the coefficient on *Year*. After controls, the average trend for securities in the survivor sample drops from 17.7 basis points in Model (1) to 5.26 basis points per month ($t = 23.16$) in Model (3). Consistent with what has already been observed in Model (2), Model (4) shows an increase in trend coefficients across quintiles of passive institutional ownership growth. This growth, however, is not monotonic. For the first quintile, the average R^2 trend is 5.42 basis points per month ($t = 11.19$). The trend coefficient grows monotonically from the second (3.88 bps per month; $t = 9.78$) to the third (4.95 bps per month; $t = 12.33$), fourth (5.79 bps per month; $t = 14.14$), and fifth (7.12 bps per month; $t = 17.75$) quintiles. In addition, Wald test coefficients of 725.43 and 204.72 fail to reject the null that the trend across all passive ownership quintiles is statistically the same and that the trend from stocks in the top passive ownership quintile is higher than the trend from stocks in the bottom quintile. The increase in R^2 trend coefficients and Wald tests support our hypothesis and suggest that the primary cause for the sustained increase in average R^2 since the early 1990s is the rise of *Passive Institutional Ownership*.[9,10]

4. Influence of passive institutional ownership on R^2

In addition to our main tests on the average trend of individual R^2s, we design a supplementary test where annual changes in *Passive Institutional Ownership* are regressed on annual changes in R^2. This test serves two purposes. First, it determines the influence of passive institutional ownership increases on R^2 increases in comparison to changes in other variables. In addition, it provides an opportunity to test the relation between *Passive Institutional Ownership* increases and R^2 increases on both the full and the survivor samples. In this way, we mitigate the effects of a possible survivor bias in our main results that, by construction, only include securities listed during the entire 1993–2010 period (i.e., the survivors).

To determine the sensitivity of R^2 increases to *Passive Institutional Ownership* increases, we conduct first difference pooled regressions with two-way fixed effects, two-way standard error clustering (e.g., Petersen, 2009; Thompson, 2011), and White (1980) heteroskedasticity-consistent standard errors. We choose first difference as opposed to level regressions for two reasons. First, given that our interest is to determine whether passive institutional ownership was a determining factor in R^2's secular increase, it is more appropriate to look at how R^2 increases respond to increases in passive institutional ownership and other factors than at levels of these variables. In addition, by taking first differences, we render the individual R^2 series stationary making them fit for cross-sectional analysis.

Table 5 reports coefficients and corresponding *t*-statistics from first difference regressions of the natural logarithm of individual R^2s on the natural logarithm of *Passive Institutional Ownership* and controls for observations in the full sample.

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[9] For the sake of brevity, we do not report the regression coefficients of the control variables in Models (2) and (4) in detail, but these coefficients have been tabulated and are available on request from the authors.

[10] We put the inference drawn from Table 4 to the test by fitting Models (2) and (4) on securities sorted on variables other than passive institutional ownership. Specifically, we sort securities on *Market Capitalization* and *Noise* (i.e., autocorrelation coefficients). In doing so, we are testing the alternative that comovement has risen due to sustained increases in correlated trading or sustained reductions in market frictions. Unlike securities sorted on passive institutional ownership growth, the trend coefficients of securities sorted on *Market Capitalization* growth do not increase monotonically. This is inconsistent with an alternative hypothesis where the primary cause for the sustained increase in average R^2 would be driven by only the largest firms. In addition, we sort variables on *Noise*, a proxy for the effects of market friction on security returns. Here, we examine the alternative that increasing comovement could be a consequence of faster information diffusion. Just as was observed using *Market Capitalization* as the sorting variable, the trend coefficients of securities sorted on *Noise* changes do not increase monotonically across quintiles. The behavior of the trend coefficient across quintiles is erratic and no pattern can be identified. This is inconsistent with market frictions being responsible for comovement's increasing trend. These test results have been omitted from the manuscript for the sake of brevity, but are available for interested readers on request.

Table 5

Cross-sectional determinants of changes in stock return

This table presents the results of panel regressions of the change in comovement on change in passive institutional ownership and the control variables using the full sample from 1993 to 2010. The regressions include time, firm, and industry fixed effects. The standard errors are clustered by firm and time, and robust *t*-statistics are presented in parentheses.

		1993–2010			2004–2010		
		(1)	(2)	(3)	(4)	(5)	(6)
ΔLn(Passive institutional ownership)		1.19***	1.12***	1.10***	1.85***	1.67***	1.66***
		(3.83)	(3.82)	(3.77)	(7.52)	(5.24)	(5.33)
ΔLn(ETF ownership)					0.02	0.02	0.02
					(0.75)	(0.83)	(0.83)
ΔLn(Num. of index memberships)				−0.05***			−0.07***
				(−4.86)			(−4.25)
Deletions from	large-cap indexes	0.17**	0.18**		0.05	0.06	
		(2.03)	(2.23)		(0.69)	(0.88)	
	mid-cap. indexes	0.08**	0.09**		0.13**	0.14**	
		(2.08)	(2.16)		(2.07)	(2.20)	
	small-cap indexes	0.01	0.02		−0.03	−0.02	
		(0.13)	(0.30)		(−0.27)	(−0.18)	
	low-priced stocks	0.18***	0.11***		0.15**	0.09	
		(4.13)	(2.79)		(2.49)	(1.63)	
Additions to	large-cap indexes	−0.15***	−0.15***		−0.14***	−0.14***	
		(−4.34)	(−4.21)		(−3.09)	(−3.14)	
	mid-cap. indexes	−0.06	−0.06		−0.07	−0.07	
		(−1.34)	(−1.27)		(−1.62)	(−1.52)	
	small-cap indexes	−0.13***	−0.14***		−0.24***	−0.25***	
		(−4.56)	(−4.64)		(5.78)	(−6.19)	
	low-priced stocks	0.01	0.03		−0.01	0.01	
		(0.31)	(0.69)		(−0.08)	(0.11)	
ΔLn(Market capitalization)		0.68***	0.49***	0.50***	0.66***	0.47***	0.48***
		(17.52)	(11.52)	(11.28)	(7.87)	(5.86)	(5.77)

(*Continued*)

Table 5 (*Continued*)

Cross-sectional determinants of changes in stock return

	1993–2010			2004–2010		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLn(Sales per share comovement)	−0.004	−0.004	−0.004	0.01	0.01	0.01
	(−0.83)	(−0.84)	(−0.80)	(0.70)	(0.65)	(0.67)
ΔLn(Active institutional ownership)	0.49***	0.34*	0.34*	0.20	0.01	0.02
	(2.79)	(1.76)	(1.78)	(0.59)	(0.02)	(0.05)
ΔLn(Number of analysts)	−0.01	−0.03	−0.03	−0.002	−0.01	−0.01
	(−0.49)	(−0.99)	(−1.00)	(−0.08)	(−0.62)	(−0.61)
ΔLn(Noise)		−0.55***	−0.56***		−0.30	−0.30
		(−3.55)	(−3.57)		(−1.42)	(−1.44)
ΔLn(Share volume)		0.01	0.01		0.09	0.09
		(0.49)	(0.47)		(0.84)	(0.84)
ΔLn(Turnover)		0.09*	0.10*		−0.04	−0.04
		(1.78)	(1.84)		(−0.27)	(−0.25)
ΔLn(Inverse Amihud measure)		0.08***	0.08***		0.09*	0.09*
		(3.04)	(3.01)		(1.93)	(1.89)
ΔLn(Number of trading days)		0.18	0.20		0.47	0.47
		(0.77)	(0.82)		(0.71)	(0.71)
Intercept	−0.35	−0.35	−0.34	0.14	0.10	0.09
	(−1.30)	(−1.28)	(−1.30)	(0.39)	(0.26)	(0.24)
Number of observations	46,318	46,318	46,319	19,523	19,523	19,523
R^2 (with fixed effects)	0.143	0.149	0.149	0.195	0.203	0.203
R^2 (w/o fixed effects)	0.031	0.043	0.042	0.022	0.046	0.046

*, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Columns 1–3 in Table 5 report the regression coefficients and test statistics of the model specifications that exclude ETF ownership. These regressions are fit on the entire 1993–2010 period. Columns 4–6 in Table 5 report coefficients and test statistics including ETF ownership. Because the change in ETF ownership data is only available since 2004, regression coefficients in these columns only apply from 2004 to 2010.

Given that the continuous variables in our analysis are first differenced and log transformed and that annual changes are small, we interpret the coefficient estimates of these variables as elasticities. Therefore, with the exception of index and investment style additions and deletion dummies, the coefficients in Table 5 show the percentage change in R^2 associated with a 1% increase in each independent variable.

The regression coefficients and test statistics in Table 5 are consistent with a passive institutional ownership explanation of the shift in comovement's trend. Coefficient estimates for the changes in passive institutional ownership are by far the largest and most significant of all. Annual changes in *Passive Institutional Ownership* are positively related to annual R^2 changes in all of the model specifications. Consider the change in *Passive Institutional Ownership* in columns 1–3. The response of R^2 to a 1% increase in *Passive Institutional Ownership* is 1.19%, 1.12%, and 1.10% (t = 3.83, 3.82, and 3.77, respectively). During the most recent period, 2004–2010, the response is even stronger. It is 1.85%, 1.67%, and 1.66% (t = 7.52, 5.24, and 5.33, respectively).

The coefficient estimates in columns 4–6 show that although positive, the effect of *ETF Ownership* changes on R^2 changes is economically and statistically insignificant. Contrary to Israeli, Lee and Sridharan (2015), we find no evidence that ETF ownership increases R^2. Rather, passive ownership, in general, dominates ETF ownership in relation to R^2. This could happen because the ETF industry is still in its infancy and very small relative to the size of the equity markets.

Coefficient estimates for the correlated trading proxies are, for the most part, statistically significant and bear the expected signs suggesting that correlated trading is an important determinant of R^2. Coefficient estimates for *Number of Index Memberships* are negative and significant. The coefficient estimate for this variable in column 3 suggests that a 1% increase in index memberships results in a 5 bp ($t = 4.86$) reduction in R^2. Put a different way, a unit increase in index memberships relative to the mean (5.04) results in a 0.25% (5.04×-0.05) reduction in R^2. This implies that correlated trading from multiple index memberships is primarily the result of investors' focusing on certain indexes that fit their investment styles and not of open-ended index fund managers' accommodating net fund flows.

Just as with *Number of Index Memberships*, index fund addition and deletion dummies also suggest significant habitat and style investing effects on R^2. For example, column 1 indicates that from 1993 to 2010, deletions from large cap indexes, mid cap indexes, and the low priced stock category, occurring when prices increase above $10 per share, result in R^2 increases of 0.17% ($t = 2.03$), 0.08% ($t = 2.08$), and 0.18% ($t = 4.13$), respectively. Alternatively, additions in the large cap and small cap indexes result in R^2 reductions of 0.15% ($t = 4.34$) and 0.13% ($t = 4.56$). While the order of magnitude of additions and deletions for large cap indexes is similar, index additions have surpassed deletions in 16 of the 18 sample period years. This is a natural consequence of the rapid increase in publicly available indexes found in Wurgler (2010). With R^2-reducing additions as the dominant force, correlated trading from habitat effects should have been a hindrance, and not a cause, for comovement's positive trend.

The effect of informed market participants on R^2 changes is captured by changes in *Active Institutional Ownership* and *Number of Analysts.* Coefficient estimates for *Number of Analysts* are all statistically insignificant. According to Chakravarty (2001), institutional ownership changes convey information as long as institutional investment decisions are motivated by firm-specific information. When this happens, institutional trading should accelerate the incorporation of firm-specific news into prices (e.g., Piotroski and Roulstone, 2004). Thus, changes in *Active Institutional Ownership* should increase firm-specific volatility and reduce R^2.

This is not what we observe in column 1 of Table 5, where a 1% increase in *Active Institutional Ownership* results in a 0.49% increase in R^2 ($t = 2.79$). Although, when more control variables are included in the model, as in columns 2 and 3, the statistical significance falls to the 10% level and goes away completely from 2004 to 2010. The positive relation found in Models (1)–(3) could be related to herding and be the result of structural changes in the compensation scheme of financial managers (e.g., Rajan, 2005).[11] Alternatively, more active ownership could speed the incorporation of market-wide news into stock prices resulting in lower price delays and higher comovement. In any case, comovement's relation with passive ownership remains economically and statistically strong in all model specifications while its relation with active ownership does not. In the next section, we examine the impact both active and passive ownership have on price informativeness.

Coefficient estimates for most market friction proxies are statistically insignificant as well, except for noise and the Amihud measure in the full 1993–2010 period. Coefficient estimates for market frictions from 2004 to 2010 are all insignificant. Table 5 results suggest that *Passive Institutional Ownership* change is the most economically and statistically significant determinant of R^2 change.

[11] Rajan (2005) suggests that a shift in compensation, from fixed to return-based, has caused a separation between financial managers' incentives and those of their clients. Until the 1970s, the incentive of U.S. financial managers, who worked primarily for banks, was to keep their client's money safe. Afterward, with the rise of mutual funds, this incentive shifted from fulfilling fiduciary duties to outperforming other fund managers. According to Rajan (2005), the downside of more intense competition in portfolio management has been an increased incentive by financial managers to avoid penalties tied to underperformance. In this environment, many financial managers choose to herd rather than compete, thus failing to perform fundamental analysis.

5. Influence of active versus passive institutional ownership on price informativeness

The final step of our analysis consists of empirically testing the relation between passive institutional ownership and price informativeness. Given the heated debate in the literature regarding the validity of the market model R^2 as a price informativeness measure, it is important that we find that passive institutional ownership is indeed negatively related to price informativeness using proxies other than R^2. This is especially important because Jiambalvo, Rajgopal and Venkatachalam (2002) find that total institutional ownership improves the extent that prices incorporate information about future earnings implying a positive relation between institutional ownership and price informativeness.

To test the empirical relation between passive institutional ownership and price informativeness, we replicate the tests in Jiambalvo, Rajgopal and Venkatachalam (2002) while breaking down institutional ownership into its active and passive components. Table 6 summarizes the results from measuring the extent that stock prices lead earnings conditional on active and passive institutional ownership. The method to assess the extent that stock prices reflect the proportion of information in future versus current earnings comes from Kothari and Sloan (1992). They find stock prices contain information that take some time to be reflected into accounting earnings and suggest the following equation:

$$R_{it,t-\tau} = \omega_0 + \omega_{1(\tau)} (E_{it}/P_{it-\tau}) + \varepsilon_{it-\tau}. \tag{5}$$

If current earnings information has been efficiently incorporated into past prices, the coefficient $\omega_{1(\tau)}$ will get smaller as the time interval τ gets smaller. Thus, in a two-period scenario, the expression $\omega_{1(\tau=2)} > \omega_{1(\tau=1)}$ implies that current information has been incorporated into past prices. The wider the distance between these coefficients, the more past prices reflect current information. The difference can also be expressed as the ratio $\omega_{1(\tau=2)}/\omega_{1(\tau=1)}$ which is useful as it reflects the relative difference between the two coefficients. Analogous to $\omega_{1(\tau=2)} > \omega_{1(\tau=1)}$, a ratio of $\omega_{1(\tau=2)}/\omega_{1(\tau=1)}>1$ indicates information about earnings is incorporated into past prices earlier. The higher the ratio, the more information about current earnings that has been incorporated into past stock prices. Conversely, a ratio less than 1 is indicative of lower price efficiency, where information takes longer to be incorporated into the price.

To examine the influence of the level of active and passive institutional ownership on earnings predictability, we interact the earnings term with the levels of active and passive institutional ownership in place at the beginning of the return accumulation period. That is, we modify Equation (5) as follows:

$$\begin{aligned} R_{it-\tau,t} = \omega_0 &+ \omega_{1(\tau)} E_{it} + \omega_{2(\tau)} (E_{it} xPASS_{it-\tau}) + \omega_{3(\tau)} (E_{it} xNONPASS_{it-\tau}) \\ &+ \omega_{4(\tau)} (E_{it} xNANAL_{it-\tau}) + \omega_{5(\tau)} (E_{it} xMB_{it-\tau}) \end{aligned}$$

Table 6

Tests of price informativeness

This table presents the generalized least squares estimates using a seemingly unrelated regression specification of the relation between earnings and stock returns conditional on the percentage of passive and nonpassive institutional ownership. t-Statistics are denoted in parentheses. The differences of the ωs ($\omega_{n(\tau=2)} - \omega_{n(\tau=1)}$) of interest comparing coefficients under the two return horizons are presented with the ratios of the two ($\omega_{n(\tau=2)}/\omega_{n(\tau=1)}$) in curved brackets. The Wald statistic p-values (null hypothesis of the two values are equal) are presented in square brackets under the differences. $R_{t-1,t}$ ($R_{t-2,t}$) is the stock return measured over the period $t-1$ ($t-2$) to t. *PASS* is the percentage of equity shares held by passive institutional investors. *NONPASS* is the percentage of equity shares held by financial institutions not classified as passive. *SIZE* is the natural logarithm of the market value of equity. *LEV* is the ratio of total debt scaled by lagged total assets. *NANAL* is the number of analysts following the firm. *MB* is the market-to-book ratio and *E* is income before extraordinary items scaled by lagged total assets. Accounting information comes from Compustat, while market information comes from CRSP. The sample period is 1993–2010.

	Dependent variable		Difference: $\omega_{(\tau=2)} - \omega_{(\tau=1)}$ {Ratio: $\omega_{(\tau=2)}/\omega_{(\tau=1)}$}
	$R_{t-1,t}$	$R_{t-2,t}$	[Wald statistic p-value, null: $\omega_{(\tau=2)} = \omega_{(\tau=1)}$]
Panel A: $R_{it-\tau,t} = \omega_0 + \omega_{1(\tau)}E_{it} + \omega_{2(\tau)}(E_{it}xPASS_{it-\tau}) + \omega_{3(\tau)}(E_{it}xNONPASS_{it-\tau}) + \omega_{4(\tau)}(E_{it}xNANAL_{it-\tau}) + \omega_5(\tau)(E_{it}xMB_{it-\tau}) + \omega_{6(\tau)}(E_{it}xLEV_{it-\tau}) + \omega_{7(\tau)}(E_{it}xSIZE_{it-\tau}) + \varepsilon_{it(\tau)}$			
E_{it}	0.902	0.088	
	(40.24)	(3.33)	
$E_{it}xPASS_{it-\tau}$	0.665	0.242	−0.423 {0.364}
	(4.88)	(1.23)	[0.026]
$E_{it}xNONPASS_{it-\tau}$	0.160	2.490	2.330 {15.563}
	(1.03)	(11.66)	[0.000]
$E_{it}xNANAL_{it-\tau}$	−0.002	−0.004	
	(−6.89)	(−8.16)	
$E_{it}xLEV_{it-\tau}$	0.922	2.582	
	(8.96)	(15.58)	
$E_{it}xMB_{it-\tau}$	0.246	1.753	
	(11.26)	(36.37)	
$E_{it}xSIZE_{it-\tau}$	0.128	0.323	
	(1.26)	(20.13)	
E_{it-1}	−0.800	0.540	
	(−44.61)	(2.21)	
Intercept	1.151	0.306	
	(57.94)	(76.06)	
SUR adjusted-R^2	0.064	0.076	
Number of observations	61,539	61,539	
E_{it}	0.821	−0.006	
	(36.24)	(−0.23)	
$E_{it}xPASSQ2_{it-\tau}$	0.592	0.914	0.322 {1.544}
	(3.79)	(3.86)	[0.191]

(*Continued*)

Table 6 (*Continued*)

Tests of price informativeness

	Dependent variable		Difference: $\omega_{(\tau=2)} - \omega_{(\tau=1)}$ {Ratio: $\omega_{(\tau=2)}/\omega_{(\tau=1)}$}
	$R_{t-1,t}$	$R_{t-2,t}$	[Wald statistic p-value, null: $\omega_{(\tau=2)} = \omega_{(\tau=1)}$]
Panel B: $R_{it-\tau,t} = \omega_0 + \omega_{1(\tau)}E_{it} + \omega_{2(\tau)}(E_{it}xPASSQ2_{it-\tau}) + \omega_{3(\tau)}(E_{it}xPASSQ3_{it-\tau}) + \omega_{4(\tau)}(E_{it}xPASSQ4_{it-\tau}) + \omega_{5(\tau)}(E_{it}xPASSQ5_{it-\tau}) + \omega_{6(\tau)}(E_{it}xNONPASSQ2_{it-\tau}) + \omega_{7(\tau)}(E_{it}xNONPASSQ3_{it-\tau}) + \omega_{8(\tau)}(E_{it}xNONPASSQ4_{it-\tau}) + \omega_{9(\tau)}(E_{it}xNONPASSQ5_{it-\tau}) + \omega_{10(\tau)}(E_{it}xNANAL_{it-\tau}) + \omega_{11(\tau)}(E_{it}xMB_{it-\tau}) + \omega_{12(\tau)}(E_{it}xLEV_{it-\tau}) + \omega_{13(\tau)}(E_{it}xSIZE_{it-\tau}) + \varepsilon_{it(\tau)}$			
$E_{it}xPASSQ3_{it-\tau}$	0.414	0.212	−0.202 {0.512}
	(5.08)	(1.94)	[0.101]
$E_{it}xPASSQ4_{it-\tau}$	0.576	0.383	−0.193 {0.665}
	(5.11)	(2.56)	[0.255]
$E_{it}xPASSQ5_{it-\tau}$	0.377	−0.404	−0.781 {−1.072}
	(3.12)	(−2.44)	[0.000]
$E_{it}xNONPASSQ2_{it-\tau}$	2.495	6.543	4.048 {2.622}
	(7.23)	(13.01)	[0.000]
$E_{it}xNONPASSQ3_{it-\tau}$	0.327	1.087	0.760 {3.324}
	(3.85)	(9.49)	[0.000]
$E_{it}xNONPASSQ4_{it-\tau}$	0.371	1.490	1.119 {4.016}
	(3.60)	(10.42)	[0.000]
$E_{it}xNONPASSQ5_{it-\tau}$	0.076	1.488	1.412 {19.579}
	(0.70)	(10.28)	[0.000]
$E_{it}xNANAL_{it-\tau}$	−0.003	−0.005	
	(−8.87)	(−10.70)	
$E_{it}xLEV_{it-\tau}$	0.840	2.362	
	(8.18)	(14.29)	
$E_{it}xMB_{it-\tau}$	0.164	1.540	
	(5.39)	(31.50)	
$E_{it}xSIZE_{it-\tau}$	0.129	0.324	
	(11.23)	(20.16)	
E_{it-1}	−0.808	0.018	
	(−45.14)	(0.73)	
Intercept	0.146	0.292	
	(55.27)	(71.62)	
SUR adjusted-R^2	0.067	0.084	
Number of observations	61,539	61,539	

$$+\,\omega_{6(\tau)}\,(E_{it}xLEV_{it-\tau}) + \omega_{7(\tau)}\,(E_{it}xSIZE_{it-\tau}) + \varepsilon_{it(\tau)}, \tag{6}$$

where *NONPASS* and *PASS* represent the percentage of active (i.e., nonpassive) and passive institutional ownership, respectively. Following Jiambalvo, Rajgopal and Venkatachalam (2002), we define earnings ($E_{i,t}$) as income before extraordinary items scaled by lagged total assets and estimate Equation (6) for both $\tau = 1$ and $\tau = 2$ using seemingly unrelated regressions (SURs) and conduct Wald tests of the null $\omega_{2(\tau=2)} = \omega_{2(\tau=1)}$ and $\omega_{3(\tau=2)} = \omega_{3(\tau=1)}$. We control for factors that affect the relation between price and earnings by including leverage (*LEV*) and the book-to-market ratio (*MB*) in the regression equation. Also consistent with Jiambalvo, Rajgopal and Venkatachalam (2002), we control for the endogeneity related to the possibility that institutional investors are attracted to firms with more informative prices by including firm size (*SIZE*) and the number of analysts following the firm (*NANAL*).[12]

Panel A of Table 6 reports the results of estimating Equation (6). We estimate this equation for two intervals ($\tau = 1$ and 2) as SURs in order to control for the correlations in the error terms of the two regressions and also to directly compare coefficient estimates since the regressions are estimated as a system. Our primary focus is to compare the coefficients $\omega_{2(\tau = 2)}$ and $\omega_{2(\tau = 1)}$ that are the coefficients on the interaction of passive institutional ownership and earnings. The estimate of $\omega_{2(\tau = 1)}$ is 0.665, while $\omega_{2(\tau = 2)}$ is 0.242 (the Wald statistic to test the equality of $\omega_{2(\tau = 2)}$ and $\omega_{2(\tau = 1)}$ is 4.93, $p = 0.026$). These results are consistent with our hypothesis that passive institutional investors delay the incorporation of firm-specific earnings information into stock prices, thus degrading price informativeness in the market. Alternatively, $\omega_{3(\tau = 1)}$ is 0.160, while $\omega_{3(\tau = 2)}$ is 2.490 (the Wald statistic to test the equality of $\omega_{3(\tau = 2)}$ and $\omega_{3(\tau = 1)}$ is 118.66, $p = 0.000$). These coefficients are consistent with Jiambalvo, Rajgopal and Venkatachalam (2002) and suggest that active financial institutions are sophisticated investors as earnings information is incorporated faster when active institutional ownership is relatively high.

In addition to the interaction analysis reported in Panel A of Table 6, we test the prediction that the ratio of $\omega_{n(\tau = 2)}$ to $\omega_{n(\tau = 1)}$ increases across quintiles of active institutional ownership and declines across quintiles of passive institutional ownership. To conduct this test, we modify Equation (5) and allow the coefficient on earnings to vary as a function of the quintile membership of active and passive institutional ownership as follows:

$$\begin{aligned} R_{it-\tau,t} = \omega_0 &+ \omega_{1(\tau)} E_{it} + \omega_{2(\tau)} (E_{it} x PASSQ2_{it-\tau}) + \omega_{3(\tau)} (E_{it} x PASSQ3_{it-\tau}) \\ &+ \omega_{4(\tau)} (E_{it} x PASSQ4_{it-\tau}) + \omega_{5(\tau)} (E_{it} x PASSQ5_{it-\tau}) \\ &+ \omega_{6(\tau)} (E_{it} x NONPASSQ2_{it-\tau}) + \omega_{7(\tau)} (E_{it} x NONPASSQ3_{it-\tau}) \\ &+ \omega_{8(\tau)} (E_{it} x NONPASSQ4_{it-\tau}) + \omega_{9(\tau)} (E_{it} x NONPASSQ5_{it-\tau}) \\ &+ \omega_{10(\tau)} (E_{it} x NANAL_{it-\tau}) + \omega_{11(\tau)} (E_{it} x MB_{it-\tau}) \\ &+ \omega_{12(\tau)} (E_{it} x LEV_{it-\tau}) + \omega_{13(\tau)} (E_{it} x SIZE_{it-\tau}) + \varepsilon_{it(\tau)}. \end{aligned} \tag{7}$$

[12] The variables in this regression are consistent with those in Jiambalvo, Rajgopal and Venkatachalam (2002, pp. 131–132, Table 3). While *NONPASS* and *PASS* have a correlation coefficient of 0.47, the average variance inflation factor of the regressions is only 2.35 indicating the lack of any multicollinearity problems.

The results of estimating this modified version of Equation (5) across quintiles are reported in Panel B of Table 6. For all of the coefficients of the interaction between quintiles of active institutional ownership and earnings, we find that the coefficients increase with the length of the interval in which the returns are measured (e.g., $\omega_{6(\tau = 2)} > \omega_{6(\tau = 1)}$). In addition, the ratios increase monotonically across quintiles suggesting that earnings predictability increases with the percentage of active institutional ownership in the stock. These results are consistent with Jiambalvo, Rajgopal and Venkatachalam's (2002) results regarding overall institutional ownership and its ability to increase price informativeness.

Alternatively, for the coefficients on the interaction between passive institutional ownership and earnings, the ratios generally decline across quintiles starting at 1.544 for Quintile 2 and ending at −1.072 for Quintile 5. The Wald statistic to test the equality of $\omega_{2(\tau = 2)}$ and $\omega_{2(\tau = 1)}$ in Quintile 2 is 1.71 ($p = 0.191$), while the Wald statistic to test the equality of $\omega_{5(\tau = 2)}$ and $\omega_{5(\tau = 1)}$ in Quintile 5 is 19.23 ($p = 0.000$). In another test, not reported in detail here, we find the ratio for the fifth quintile is statistically smaller than the ratio in the second, third, and fourth quintiles (*p*-values of 0.0063, 0.0022, and 0.0002, respectively).

In essence, Jiambalvo, Rajgopal and Venkatachalam (2002) find that the extent that stock prices lead earnings is positively related to the percentage of institutional ownership. The results in Table 6 suggest that this is only true among stocks owned by institutions following active (i.e., nonpassive) investment strategies. The percentage of passive institutional ownership when $\tau = 2$ is actually negatively related to earnings predictability in the highest quintile of passive ownership. These results indicate passive institutional ownership is detrimental to price informativeness.

6. Concluding comments

In this study, we find a direct connection between the rise of stock return comovement and the increasing dominance of passive investing in financial institutions. There is no doubt that passive investing has been a boon to U.S. retail investors providing an inexpensive and time-efficient manner to invest in financial securities, but we demonstrate that the tradeoff appears to be higher stock return correlations and lower price efficiency.

The rise of passive investing can be traced back to the "challenge to common sense" made by Paul Samuelson on the inaugural issue of the *Journal of Portfolio Management* (e.g., Samuelson, 1974). In this now iconic piece, Samuelson cast doubt on the possibility that anyone could consistently beat the market and challenged the investment industry to create an instrument that would track the S&P500 Index. Fast forward 40 years and we find Samuelson's challenge being met by a passive investment industry that not only owns about half of all U.S. stock shares, but that also has some of the world's largest funds in its ranks. Passive investing owes its success to its low cost structure that has led to increasing margins thanks to regulatory change and technological innovation.

A question that emerges from the rise of passive investing is its potential consequences on market efficiency. During our investigation, we find a negative relation between passive institutional ownership and the future earnings information incorporated in a stock's price. This suggests that the rise in passive investing could have eroded price informativeness over the past two decades. However, given that information technology has simultaneously enhanced market liquidity and information diffusion, it is not clear how severe this loss has been. Grossman and Stiglitz (1980) predict that passive investing will continue to grow until the profit opportunities from mispricing exceeds the cost savings from index tracking. However, the magnitude of mispricing (e.g., arbitrage profits) required to entice active asset management could be greater than expected by market efficiency advocates due to institutional rigidities in U.S. pension plans and economies of scale in the mutual fund industry (e.g., Alti, Kaniel and Yoeli, 2012; Blitz, 2014). Until that point is met, higher passive investing could come at a cost to price informativeness.

Even though, in theory, price changes should summarize all of the information on a firm's future payoffs, how closely tied prices and information really are remains a hotly debated issue. Central to this discussion has been the use of the average market model R^2 as a price informativeness measure. While many studies argue that high R^2 is indicative of low price informativeness (e.g., Morck, Yeung and Yu, 2000; Piotroski and Roulstone, 2004; Jin and Myers, 2006), other studies oppose this idea and suggest that average R^2 measures changes in cash flow correlations (e.g., Brown and Kapadia, 2007; Irvine and Pontiff, 2009) and temporary spikes in idiosyncratic risk (e.g., Brandt, Brav, Graham and Kumar, 2010). By finding a link between average R^2 and passive investing and passive investing and earnings predictability, our study provides support for a negative relation between the market model R^2 and price informativeness.

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