THE UNIVERSITY OF TEXAS AT SAN ANTONIO, COLLEGE OF BUSINESS

Working Paper SERIES

Date May 3, 2013

WP # 0037FIN-088-2013

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EXCHANGE TRADED FUNDS, SIZE-BASED PORTFOLIOS, AND MARKET EFFICIENCY

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February 26, 2013

ABSTRACT

We examine the informational efficiency of size-based U.S. Exchange Traded Funds (ETFs) and comparable CRSP portfolios using weekly and daily returns. Compared to the CRSP portfolios, ETFs are better suited for market efficiency tests. ETFs avoid the problems created by asynchronous pricing of underlying securities. Further, their negligible bid-ask spreads greatly diminish noise due to the bid-ask bounce. Variance ratio analysis demonstrates that return autocorrelations have diminished significantly over the past decade. Granger causality tests reject the presence of lead-lag effects among size-based ETFs. Volatility spills over from large firm ETFs to those of smaller firms, and correlations increase during periods of market volatility. We confirm these spillovers by examining implied volatilities derived from ETF option prices.

JEL Classification: G15

Keywords: Exchange Traded Funds, Market efficiency

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I. Introduction

Exchange Traded Funds (ETFs) have become extremely popular instruments for asset allocation and liquidity trading, and concerns have been raised that ETF trading and related arbitrage activity may contribute to overall market volatility. The joint reports of the CFTC-SEC (2010a and 2010b) on the May 6, 2010 “flash crash” and ongoing academic research highlight these concerns.[1] We conduct tests of informational efficiency of ETF prices data for size-based Exchange-Traded Funds (ETFs); the ETFs we consider are the S&P 500 Index ETF (SPY), the S&P 400 Mid Cap Index (MDY), and the Russell 2000 Small Cap Index (IWM). We compare the results for these ETFs with those of size-based portfolios constructed using the Center for Research in Security Prices (CRSP) database. The characteristics of ETF trading allow for better tests of market efficiency compared to tests that rely on CRSP portfolios.

While the informational efficiency of financial market prices has been analyzed for some time, it remains a contentious issue among financial economists and market practitioners. Fama (1970) and Jensen (1978) note the substantial research that has not been able to reject the random walk hypothesis. However, subsequent studies such as Lo and MacKinlay (1988, 1990) find some predictability in stock returns.[2] Previous research has avoided examining daily returns of CRSP portfolios due to problems created by asynchronous prices and large bid-ask spreads for the underlying stocks. Aggregation of asynchronous prices/returns across the underlying securities for CRSP portfolios can induce spurious positive autocorrelation in returns, while the bid-ask bounce can induce spurious negative autocorrelations with the severity of the problem increasing with the magnitude of the bid-ask spread. These concerns are greatly reduced, if not

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[1] See, for example, Ben-David, Franzoni, Moussawi (2012), Bradley and Litan (2010), Chordia, Sarkar, and Subrahmanyam (2011), and Easley, de Prado, and O'Hara. (2011).

[2] See also Cochrane (2008), Conrad and Kaul (1988), Fama and French (1988), and Keim and Stambaugh (1986), among others.

eliminated, for ETFs. ETFs avoid the problem of asynchronous prices for underlying stocks, since the observed ETF price closely reflects the value of the underlying securities at that point in time. Further, given their extremely high trading volumes, ETF bid-ask spreads are negligible.[3] The size-based ETF data enable us to compare time-series results regarding returns and volatility with the more frequently studied size-based portfolios obtained from CRSP.

Using data over the 2000-2012 period, we calculate the Lo and MacKinlay (1988) variance ratios for ETFs to test for violations of the random walk hypothesis. As a baseline, we examine the relevant results for weekly returns on size-based CRSP stock portfolios using data from 1962 to 2012. First, we replicate the results reported by Lo and MacKinlay (1988) for the period 1962-1985, finding qualitatively identical results. Over the subsequent years, however, variance ratios have become much smaller and less significantly different from one, especially over the last decade. In fact, the results are insignificant for all but the portfolio of the smallest firms under study. Additionally, weekly and daily variance ratios for size-based ETFs conclusively demonstrate a lack of positive autocorrelation. Thus, a primary finding of the study is that market efficiency in U.S. equity prices has increased markedly over the past twenty-five years.

We also conduct Granger causality tests to examine the information flow among the returns of "big" and "small" firms, since lead-lag relationships among firms of differing sizes documented by prior research imply additional market inefficiencies (e.g. Lo and MacKinlay (1990), Badrinath, Kale, and Noe (1995), and Hou (2007)). Over the past decade, at the daily level, there is little evidence that the returns of the largest ETF (S&P 500 Index - SPY) lead

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[3] The grand average of yearly closing bid-ask spreads for the ETFs considered in this study is 0.073 percent, but only 0.021 percent since 2003, and even smaller in recent years.

those of two smaller-firm ETFs. Further, we do not find significant Granger causality for the CRSP size-based portfolio returns in recent data.

We also examine volatility spillovers in order to determine whether volatility is transmitted among the ETFs and CRSP size-based portfolios by estimating a modified version of the multivariate DCC-GARCH(1,1) model of Engle (2002). Our modifications include parameters for asymmetric volatility in the specification of the conditional variance, as suggested by Glosten, Jagannathan, and Runkle (1993). We also relax the assumption of normality in returns and utilize a Student-t distribution for the purposes of statistical inference. We find that, over the most recent decade, volatility spillovers persist from large to small firm ETFs and for one CRSP portfolio pair. The results are consistent with, Conrad, Gultekin, and Kaul (1991) and Henry and Sharma (1999), who find volatility shocks flow primarily from large firms to smaller ones. Additionally, we find that asymmetric volatility and rising correlation during periods of market volatility remain important features of the return-generating process for ETFs as well as the size-based portfolios. These volatility spillovers are confirmed by additional tests that utilize option implied volatilities derived from ETF option prices.

Our contributions to the literature are threefold. First, we conduct extensive tests of market efficiency: analysis of variance ratios, tests of lead-lag relationship among different firm-size portfolios, and examination of volatility spillovers. Second, we conduct these tests using sized-based ETFs, which have not been examined in this context previously. Finally, by analyzing an extended sample period from 1962-2012, we are able to provide a perspective on the increases in the efficiency of U.S. stock markets over the last five decades.

II. Relevant Literature

Fama (1970) surveys the earliest studies of autocorrelation-based tests of the random walk hypothesis and notes very few that reject it. Jensen (1978) notes the overwhelming evidence that supports the efficient markets hypothesis. However, later research indicates that some portion of stock returns may be predictable, especially in the case of stocks with lower market capitalizations. Fama and French (1988) find negative autocorrelation in returns over 3-5 year periods that is indicative of a mean reverting process that is stronger for small firms than for large firms. Lo and MacKinlay (1988, 1990) examine predictability using the variance ratio methodology and find evidence of short-term return predictability. They also demonstrate that equity prices of small firms may be significantly less efficient than those for large firms. The key insight of their analysis is that the variance in stock returns ought to be linear in time. That is, the variance of monthly returns should be approximately four times weekly returns, and so on. Violations of this relationship (variance ratios significantly different from one) imply positive serial correlation in returns that may be utilized to predict future returns and contradict the random walk hypothesis.

Following Lo and MacKinlay (1988, 1990), numerous studies utilize variance ratios to evaluate the random walk hypothesis for a wide variety of markets and securities.[4] We note a few recent studies that continue to rely on the variance ratio approach to assess market efficiency. Hoque, Kim, and Pyun (2007) find that stock prices do not follow random walks in Asian emerging markets using traditional and alternative variance ratio tests. Charles and Darné (2009) survey the extensive literature surrounding extensions of the Lo and MacKinlay (1988) variance ratio test statistics, noting potential deficiencies of the original method and subsequent

[4] An online search for studies that reference Lo and Mackinlay (1988) results in 2,260 citations, 277 of which occurred since 2010, so their findings and methodology remain as relevant as ever.

improved statistical properties of alternative individual and multiple variance ratios. Their own empirical study of the daily returns of Latin American stock indices from 1993 to 2007 rejects the random walk hypothesis, and the result is robust to several variance ratio tests. Thus, in addition to the Lo and Mackinlay (2008) variance ratios, we employ the Wright (2000) tests based on ranks and rank scores. Griffin et. al. (2010) measure variance ratios for size-based portfolios in developed countries, finding them to be significantly greater than one, especially for small firms on a weekly basis. They also report that the variance ratios for developed markets are not significantly different from those of emerging markets. O'Hara and Ye (2011) employ variance ratio tests to show that markets have not become inefficient due to market fragmentation in the U.S. Saffi and Sigurdsson (2011) examine monthly and weekly stock returns to show that "hard to borrow" stocks in the U.S. experience higher variance ratios (hence more deviations from the random walk) than those that can easily be sold short. Further research, while not explicitly using the variance ratio approach, also examines the autocorrelation for large and small firm portfolios. Conrad and Kaul (1988) find that small firm portfolio returns are autocorrelated at higher orders to a much greater extent than are large firm portfolio returns, and their results are robust to nonsynchronous trading. They also find a negative relation between portfolio firm size and the percent of realized price variation due to the variance of "expected" returns, which are estimated using an ARMA(1,1) process. Keim and Stambaugh (1986) demonstrate that small-firm stock returns experience increased serial correlation during certain periods (especially in January) and do not follow random walks.

Mech (1990) investigates five different potential causes of the autocorrelation of stock portfolios and argues that it is linked to transaction costs because price adjustment occurs more slowly in the presence of large bid/ask spreads. He notes that markets may not be perfectly efficient, but investors are not irrational since it is costly to exploit these opportunities. Llorente, Michaely, Saar, and Wang (2002) provide an explanation for autocorrelations in returns based on a theoretical model of informed trading, where speculative traders provide a continuation of returns, while hedging activity results in price reversals. The minimal bid-ask spreads of ETFs based on major market indices attract both speculators and hedgers. We therefore investigate the autocorrelation characteristics of these securities.

Badrinath, Kale, Noe (1995) present evidence that "the prices of large-firm stocks convey information regarding the prospects of smaller-firm stocks," since some firms are "institutionally favored," while others are not. Similarly, Hou (2007) provides evidence that smaller firms (especially in smaller, less favored industries) experience greater lead-lag effects in returns as compared to larger firms due to sluggish reactions to negative news. Recently, Chordia, Sarkar, and Subrahmanyam (2011) present a theoretical model where lagged large stock returns transmit information to small stocks. They provide empirical analysis of size-based CRSP deciles that supports this hypothesis.

Boudoukh, Richardson, and Whitelaw (1994) argue that prior research (including Lo and MacKinlay, 1988 and 1990) may have underestimated the extent of autocorrelation in returns induced by nontrading. They estimate "implied" cross-serial correlations that are computed as the product of two portfolios' correlations and the first-order autocorrelation of each of the portfolios. These "implied" cross-serial correlations track actual estimates very closely, leading to the conclusion that "even in a world in which large-firm returns have no information beyond that contained in small firms, there can be large amounts of lagged cross-predictability." They provide empirical support for this assertion in a study of futures contracts on small and large stock indices, finding no evidence of serial correlation in weekly futures returns.

Conrad, Gultekin, and Kaul (1991) analyze transmission of volatility across size-based portfolios and that volatility shocks flow primarily from large firms to small ones. Henry and Sharma (1999) study Australian stock returns to reach similar conclusions. We are interested in examining whether volatility spillovers across the sized-based ETFs conform to this pattern.

III. Data Description

The data for this study includes daily and weekly total returns for three ETFs from Bloomberg Professional ®. We collect daily returns (including dividends) based on the 4:00PM ET closing print for funds that track the Russell 2000 Small Cap Index (IWM), the S&P 400 Mid Cap Index (MDY), and the S&P 500 Index ETF (SPY). The ETF sample includes return data from the inception of trading in IWM (May 26, 2000) to September 26, 2012. The daily return data for the ETFs is converted to weekly returns, as in Lo and MacKinlay (1988) and consistent with prior research, on a Wednesday to Wednesday basis. Weekly summary statistics for the ETFs are presented in Panel A of Table 1. We also obtain return data for the three CRSP portfolio Quintiles (Q1, Q3, and Q5) sorted on market capitalization from the website of Dr. Kenneth French (the portfolios are rebalanced annually in June of each year). The correlation matrix in Panel B includes correlations with the three ETFs and their "corresponding" CRSP portfolios. Based on these correlations, the ETFs generally represent reasonable proxies for the size-based portfolios.[5] As above, the daily CRSP data is converted to weekly observations, beginning on September 6, 1962 and ending on September 26, 2012 for a total of 2,612 weekly observations. The average number of stocks in each weekly observation is 5,744, while the median is 6,291, and ranges from a low of 2,037 in November 1963 to a high of 9,149 during the internet bubble

[5] Although the small cap Russell ETF (IWC) is correlated with the smallest CRSP portfolio at a slightly higher level than IWM (0.95 vs 0.93), data for this ETF is available only since its inception in August 2005. We use IWM rather than IWC since it has a longer time-series available. IWC is highly correlated with IWM and yields similar results.

in November of 1997. The final weekly sample contains 5,643 firms.

The earliest portion of this sample (from September 6, 1962 to December 12, 1972) is virtually identical to that of Lo and MacKinlay (1988). Lo and MacKinlay utilize only data from NYSE/AMEX firms, reporting the number of stocks in their sample between 2,036 and 2,720. Our sample contains NASDAQ firms beginning in December 1972. Remarkably, despite a doubling of the number of firms due to the inclusion of NASDAQ stocks, the variance ratio tests below confirm that the sample is qualitatively very similar to that of Lo and MacKinlay in terms of autocorrelation. Summary statistics for the weekly CRSP portfolio returns are provided in Panel A of Table 2, while correlation matrices are contained in Panel B. The portfolio mean returns decline monotonically with size for the whole sample, although standard deviations do not. This observation of a potentially negative relation between risk and return has been noted previously, but it is not the focus of the current study.[6] There are also substantial deviations in portfolio returns among the sub-periods. The correlation matrices in Panel B demonstrate the increasing correlations among portfolios across time, as noted by Wurgler (2010). The correlations for May 2000 to September 2012 are uniformly higher than those of the entire sample, which may be the result of the continuing trend towards "passive" index investing and the"benchmarking" of portfolio managers.

In order to examine the volatility dynamics and arbitrage relationships among the ETFs and related derivative instruments, we also analyze daily options implied volatility data. We obtain average call and put implied volatility estimates (for "at the money" options) for constant thirty day maturity options for each of the ETFs from Bloomberg Professional®. The data is

[6] For evidence of this phenomenon, see Goyal and Santa-Clara (2003), Haugen (2010), and Hibbert, Daigler, and Duoiyet (2008).

available from January 10, 2005 to September 26, 2012. We truncate the at the one percent level at each extreme to remove the effects of outliers.

IV. Variance Ratio Tests

Weekly Variance Ratios

Following Lo and MacKinlay (1988), we estimate weekly variance ratios in the presence of heteroskedasticity. Table 3 presents the results for the ETF sample and contains variance ratios for the three ETFs under study: the Russell 2000 Index (IWM), the S&P 400 MidCap Index (MDY), and the S&P 500 Index (SPY). During the period from 2000 to 2012, the random walk hypothesis cannot be rejected for these securities since there is no evidence of positive autocorrelation for any of the ETFs over any *(q)* weekly timeframe. Although Lo and MacKinlay (1988, 1990) posit that their results are robust to the non-synchronous trading problem, Boudoukh, Richardson, and Whitelaw (1994) question this assertion by examining the theoretical model of non-trading that is used. They demonstrate that, when accounting for heterogeneity in portfolios, spurious autocorrelations may be present that are "two to three times higher than previously believed." They also show that returns on highly liquid futures contracts are not autocorrelated. Similarly, our finding that the variance ratios of ETFs are not significantly different from one provides evidence that even if this problem was underestimated in prior studies, it is no longer present. This supposition is supported by the fact that all of the ETFs currently trade hundreds of millions of shares per day, and bid-ask spreads consistently amount to a penny or less in recent years.

We also examine variance ratios for three size-based CRSP quintiles over the years from 1962 to 2012, and the results are contained in Table 4. Panel A contains the results for the early sample of Lo and Mackinlay (1962 to 1985). In spite of the doubling of the database to include the NASDAQ firms, the variance ratios and *z*(q)* (heteroskedasticity consistent) test statistics contained there are almost identical to those obtained in Table 2 of Lo and MacKinlay (1988, p. 54). As in their study, there is significant evidence of positive autocorrelation in returns (variance ratios greater than one) for all three of the portfolios. The minor differences are likely due to the expansion of the sample to include NASDAQ firms. For example, the variance ratio of 1.38 in the first line of Table 3 implies that the first-order autocorrelation in weekly returns is 38 percent (the corresponding figure was 1.42 in Panel A of Table 2 of Lo and MacKinlay (1988)). It is clear that the variance ratios are inversely related to firm size and that the magnitude of the variance ratios increases with the number of *(q)* weekly base observations that are aggregated to form the variance ratios. These results imply positive autocorrelations in weekly portfolio returns, which differ from those of Fama and French (1987), who find negative serial correlation over 3 to 5 year timeframes from 1926 to 1985.

However, the results change dramatically for the portfolios over the more recent period from 1986 to 2000 in Panel B. For each of the larger portfolios (Q3 and Q5), both the variance ratios and test statistics decline demonstrably. The *q(2)* variance ratio of the largest portfolio declines from 1.09 to 0.99, and the ratio of the central portfolio declines from 1.25 to 1.13. The variance ratios for the smallest portfolio do not change significantly, but the z-statistics are all significantly lower. These declines represents a continuation of the trend noted by Lo and MacKinlay (1988), as their results are weaker for the second half of their sample period than for the first half. For instance, the variance ratios for the two week base observation periods in Lo and MacKinlay (1988) decline for the largest (central) portfolios from 1.21 to 1.09 (1.30 to 1.27), a trend that continues in our results.

This phenomenon continues to exhibit itself in the results for the most recent period (2000-2012) that are contained in Panel C of Table 4. Positive autocorrelations among portfolios are even smaller in recent years, although they are still significant for the smallest portfolio. This result reflects the continued downward trend of variance ratios (and increased market efficiency) over time. The significant $z^*(q)$ statistics for Quintile 1 (Q1) indicate that information continues to be impounded into smaller stock prices over extended timeframes, but the magnitudes of the variance ratios are smaller than those in earlier periods. The ratio for the largest (central) portfolio over the two week base observation period declines from 0.99 to 0.94 (1.17 to 1.05) in the 1986 – 2000 period, and the variance ratio for the smallest portfolio declines from 1.38 to 1.17.

Griffin, Kelly, and Nardari (2010) find that variance ratios in developed markets have not changed substantially over the years spanning 1994 to 2005, and that these ratios do not differ significantly from those in emerging markets. Hoque, Kim, and Pyun (2007) find similar results for Asian emerging markets using traditional and alternative variance ratio tests for weekly stock prices from 1990 to 2004. The present study, however, utilizes data solely from the U.S., where the evidence confirms greater market efficiency. The reason our results differ from these studies is most likely because of the generally lower market capitalizations in both other developed markets and those in emerging markets (variance ratios are inversely related to firm size). Also, our results using highly liquid ETF data strongly indicate market efficiency. These data are immune to any potential problems form non-synchronous trading and/or the “bid/ask bounce,” as spreads in these securities are minimal.

Lo and MacKinlay (1988) also conduct their analysis using value-weighted portfolios, and note that the results are generally weaker. This result reinforces the importance of firm size in measurements of serial correlation. In unreported results, we have conducted the same tests over their sample period to confirm that result and then extend the sample to 2012. As in their study, the results are uniformly weaker for the value-weighted portfolios than those for equal-weighted portfolios.

Daily Variance Ratios

In light of the evidence of increased in market efficiency demonstrated in the prior section, we examine autocorrelation in stock returns using daily data for the most recent time period under study (2000 – 2012). Previous research has examined variance ratios using weekly returns rather than daily returns because of the potential positive serial correlation induced by asynchronous prices for individual securities in a portfolio. However, since ETFs are directly traded as a single instrument in contrast to CRSP portfolios, the observed ETF prices closely reflect the value of each of the underlying securities at that point in time. Another reason for using weekly rather than daily returns is to minimize the effect of the bid-ask bounce which can create spurious negative serial correlation of returns. ETFs are highly liquid instruments with negligible bid-ask spreads. Hence, the bid-ask bounce should be of minimal concern for these securities. In the recent decade, bid-ask concerns are potentially considerably reduced even for individual stocks given the sharp reductions in bid-ask spreads following price decimalization. For instance, Chung and Zhang (2013) report a mean (median) effective bid-ask spread of 0.85 (0.35) percent in 2007 for NASDAQ firms compared to a mean (median) of 3.19 (2.20) percent in 1999. Given this substantial reduction in bid-ask spreads[7], it is useful to compare the variance ratios for the size-based ETFs and CRSP portfolios using daily returns during the recent time period.

[7] The figures are even lower for NYSE/AMEX firms. The mean (median) effective bid-ask spread for these stocks is 0.76 (0..34) percent in 2007 for these firms compared to a mean (median) of 1.64 (0.94) percent in 1999

In addition to the Lo and MacKinlay (1988) variance ratio tests, we implement the Wright (2000) variance ratios based on ranks and signs. Wright (2000) demonstrates that these tests do not rely on the assumption of asymptotic normality when calculating probabilities. Thus they may be more powerful that standard variance ratios in the presence of nonnormal data. We utilize base observation periods of two, five, ten, and twenty days, and the results of this analysis are contained in Table 5.

For the smallest CRSP portfolio (the results in the right half of Table 5), the daily variance ratio tests confirm the weekly results of positive autocorrelation for all three of the tests over this timeframe. The variance ratio levels are generally similar for all of the tests, although the test statistics are significantly higher for the Wright (2000) tests, a potentially more powerful result. The positive autocorrelations for the smallest CRSP portfolio may be due to asynchronous trading, however. For the largest portfolio, there is some evidence of significant *negative* serial correlation over the 10-day observation period. The Variance Ratio for Q5 is 0.87 for the Lo and MacKinlay (1988) variance ratio and 0.86 for the Wright (2000) Rank Scores test, and both are significant at the five percent level. The negative z-statistics are even more prominent in the results for the ETFs, where the Lo and MacKinlay variance ratios are significantly less than one SPY in three out of four cases. The results for the Wright (2000) rank and rank scores tests show significant negative serial correlation for MDY as well, and the results for IWM indicate the same result in all but one of the variance ratio tests. The negative serial correlation observed in Table 5 is consistent with the short-term reversal effect of Jegadeesh and Titman (1995), who find short-term return reversals over three- to ten-day periods. These results are also consistent with inventory-based market microstructure models, as it may take several days for market makers to adjust their holdings following liquidity shocks.

Additionally, the presence of high levels of arbitrage activity in these securities may contribute to the return reversal process (see Ben-David, Franzoni, and Moussawi (2012)). The returns of SPY, for instance, are linked to trading in e-Mini futures, options on SPY and the S&P 500 cash index, as well as to futures options. A liquidity shock to any of these markets will eventually flow through to all of the related instruments, and this process may evolve over a longer than intra-day timeframe.

The finding of negative serial correlation might suggest the presence of a bid/ask bounce. However, as noted earlier, the bid/ask spreads for the ETFs are quite small. As a robustness check, we calculate ETF variance ratios using the midpoint of closing bid and ask quotes, and find qualitatively similar results as shown in Table 6. Thus, we conclude that the negative serial correlation in the ETF data is not induced by the bid-ask bounce.

We also compute variance ratios using value-weighted rather than equal-weighted CRSP portfolios and report these results in the right half of Table 6. The Lo and Mackinlay (1988) variance ratios indicating positive autocorrelation for the smallest CRSP portfolio (Q1) are no longer significantly different from one, indicating that the prior results may have been driven by non-synchronous trading in smaller firms. However, the potentially more powerful Wright (2000) ranks test still yields significant z-statistics. For the largest CRSP quintile, there is evidence of negative serial correlation for all of the variance ratio tests, as observed in the ETF data.

V. Granger Causality Tests

The results of the previous section demonstrate that positive autocorrelations in weekly returns among size-based portfolios have declined significantly over the past twenty-five years, especially for larger firms. Lo and MacKinlay (1990) analyze lead-lag return predictability between size-based portfolios of large and small firms. They find that cross-autocorrelations from lags of large firm returns to contemporaneous small firm returns are large, but those in the reverse direction are comparatively small. Table 7 presents a parallel analysis for our data set, and the general pattern found by Lo and MacKinlay (1990) remains intact. Panel A presents the results for the ETFs and is consistent with the significant but small negative serial correlation documented in the previous section. For the CRSP quintiles, the magnitudes of the cross-autocorrelations (in Panels B, C, and D) are slightly higher than those in Lo and MacKinlay (1990), most likely due to the inclusion of NASDAQ firms in our sample and either an increase in market efficiency or a decrease in non-synchronous trading issues. The figures below the diagonal are generally larger than those above, demonstrating that information from lagged returns flows in general from larger to smaller firms. In the periods subsequent to the Lo and Mackinlay (1988, 1990) studies (results in Panels B and C), the cross-autocorrelations continue to decline monotonically; they are smallest (and even negative for two of the portfolios) in the most recent sample. Fargher and Weigand (1998) also observe a similar decrease in the cross-autocorrelations.

In order to further examine the lead-lag relationship between large and small firm ETFs and portfolios, we model each portfolio's returns as a function of both own- and cross- lagged returns. We estimate the daily Granger-causality relationship in returns among the ETFs and the three portfolio quintiles through a vector autoregressive (VAR) model using five lags (to capture one week of return information), specified as follows:

$$RET_{i,t} = a_i + \sum_{j=1,3,5} \sum_{s=1}^{5} b_{i,j,s} RET_{j,t-s} + \varepsilon_{i,t}\,, \quad i = 1,3,5 \qquad (1)$$

where the five return lags *(s)* represent prior one through five day returns. The coefficients $b_{i,j,s}$ represent the lagged own- and cross- return relationships for each of the three portfolios *(i,j = 1, 3, and 5)* and exchange traded funds (*i,j = 1* for IWM, *3* for MDY, *5* for SPY). The VAR model is estimated using ordinary least squares with heteroskedasticity and autocorrelation consistent (Newey-West) standard errors. In order to test the significance of the lead-lag relationships, two restriction tests are employed on the coefficients, $b_{i,j,s}$ for each possible pair of *i* and *j* as follows:

$H_{o,1}$: $b_{i,j,s} = 0$ for all $s = 1$ to 5, and

$H_{o,2}$: $\Sigma b_{i,j,s} = 0$.

The first null hypothesis tests that all of the coefficients on lagged returns are jointly equal to zero. The second null hypothesis tests that the sum of all the coefficients on lagged returns is equal to zero. We will refer to these tests as the “joint” and “sum” tests, respectively. The size of the sum of the coefficients in the sum test provides some indication of the economic significance of the Granger causality.

We estimate the daily Granger causality relationships among the three size-based ETFs, and the results of these estimations are contained in Panel A of Table 8. We are able to analyze daily data since the potential for asynchronous trading problems is much lower in the era of decimalization and vastly increased trading volume. The results indicate a clear absence of lead-lag relationships in these highly liquid securities. None of the coefficient restriction tests can be rejected at any of the traditional levels of statistical significance. These results, which are immune to potential non-synchronous trading issues and the bid/ask bounce, strongly indicate that the random walk hypothesis cannot be rejected.

Parallel results for the CRSP portfolios are presented in Panel B, and once again there is no evidence of a lead-lag relationship among big and small firms. In contrast, Chordia, Sarkar, and Subrahmanyam (2011) document significant "big to small" lagged return transmission from 1986 to 2007, at least for the biggest and smallest CRSP deciles. But our results are obtained using only post-2000 data, so the results are not inconsistent. In unreported results, we do find evidence of "big to small" Granger causality for CRSP portfolios from 1985 to 2000. In sum, these results provide a parallel analysis to that of the variance ratios conducted in Section IV. While there may have been statistically and economically observable market inefficiencies regarding size-based portfolio in prior decades, these potential profit opportunities have all but disappeared. The results once again suggest that the cross-autocorrelations documented by Lo and MacKinlay (1990) have attenuated over time.

VI. Volatility Spillover Analysis

The Multivariate DCC-GARCH(1,1) Model

In addition to our examination of the market efficiency of returns, we are also interested in the relationships among size-based portfolio and ETF return volatilities given the concerns that trading in ETFs may induce market volatility. Conrad, Gutelkin, and Kaul (1991) find that innovations to the volatilities of large firms predict future return own- volatility and that of smaller firms, while volatility does not "spill over" in the opposite direction. In order to examine these relationships in more recent time periods, we estimate a modified version of the multivariate DCC-GARCH(1,1) model of Engle (2002) for the three ETFs as well as the equal-weighted CRSP portfolios representing the first, third, and fifth quintiles of market capitalization. The analysis is conducted for the most recent sample, from 2000 to 2012, when the ETF data is available. The mean equations are based on the vector autoregressions estimated in Equation (1), using daily data with five lags (to account for one week of return information).

The multivariate conditional variance system of these estimations is represented as follows:

$$\boldsymbol{\varepsilon_t} = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{3,t} \\ \varepsilon_{5,t} \end{pmatrix} |\boldsymbol{\Omega}_{t-1} \sim Student - t(0, \boldsymbol{H_t}, \nu), \quad \boldsymbol{H_t} = \boldsymbol{D_t R_t D_t}\text{ , }where \tag{2}$$

$\boldsymbol{D_t}$ is a three-by-three diagonal matrix of time-varying standard deviations from univariate GARCH models, $\boldsymbol{R_t}$ is the three-by-three time-varying correlation matrix, and $\boldsymbol{\Omega}_{t-1}$ represents the information set available at time *t* – *1*. The conditional variance matrices are calculated using the following equations:

$$\boldsymbol{H_{ij,t}} = \boldsymbol{Q_{ij,t}} \sqrt{\boldsymbol{H_{ii.t} H_{jj,t}}} \Big/ \sqrt{\boldsymbol{Q_{ii,t} Q_{jj,t}}}, \quad where \tag{3}$$

$$\boldsymbol{H_{ii,t}} = c_{ii} + \sum_{j=1}^{3} a_{ij} u_{j,t-1}^2 + b_i \boldsymbol{H_{ii,t-1}} + d_i u_{i,t-1}^2 \boldsymbol{I}_{\boldsymbol{u_i}<0}(u_{i,t-1}), \ and \tag{4}$$

$$\boldsymbol{Q_t} = (1 - \alpha_i - \beta_i)\boldsymbol{Q_0} + \alpha_i u_{i,t-1} u'_{i,t-1} + \beta_i \boldsymbol{Q_{t-1}}, \ and \tag{5}$$

$\boldsymbol{Q_0}$ is the unconditional correlation matrix. The conditional variance Equation (4) contains a constant term c_i, a volatility spillover term a_{ij} , a GARCH term b_i, as well as a dummy variable term (d_i) for asymmetric volatility as suggested by Glosten, Jagannathan, and Runkle (1993, hereafter GJR). The evolution of conditional correlation is described by the dynamic conditional correlation (DCC) Equation (5), which contains parameters α_i and β_i that represent the relationship between conditional correlation and lagged volatility and a decay factor, respectively. The main purpose of this equation is to provide the correlation matrices necessary for Equation (3). As long as the sum of α_i and β_i is less than one, conditional correlation will evolve as a mean-reverting process since the sum of these terms reflect the persistence of high conditional correlation.

We estimate the parameters of Equations (3) through (5) simultaneously using the log-likelihood function for the Student-t distribution, that is derived by Orskaug (2009):

$$\ln\big(L(\theta)\big) = \sum_{t=1}^{T}\left(ln\left[\Gamma\left(\frac{\nu+n}{2}\right)\right] - ln\left[\Gamma\left(\frac{\nu}{2}\right)\right] - \frac{n}{2} ln[\pi(\nu-2)] - \frac{1}{2} ln[|\boldsymbol{D_t R_t D_t}|] \right.$$

$$\left. - \frac{\nu+n}{2} ln\left[1 + \frac{\boldsymbol{a_t^T D_t^{-1} R_t^{-1} D_t^{-1} a_t}}{\nu-2}\right]\right), \qquad where\ \boldsymbol{a_t} = \boldsymbol{H_t^{1/2}} u_t \tag{6}$$

The parameter vector θ in this case is composed of two groups of coefficients, one for the univariate GARCH models and another for the parameters estimated in the dynamic conditional correlation Equation (5). The Student-*t* parameter for shape (ν) and the number of assets (n) are also included in the function. One significant advantage of this estimation procedure is that coefficients representing asymmetric volatility (d_i) are modeled explicitly, so that we can examine the effects of negative returns on volatility. In the GJR framework, positive coefficients for d_i reflect higher volatility in the presence of negative returns. Additionally, we can examine the volatility transmission process across portfolios and ETF securities by testing the significance of the volatility spillover coefficients a_{ij}. The coefficients a_{ij} (where $i < j$) are of particular interest since they indicate volatility spillover from the portfolio of larger firms (ETFs) j to the portfolio of smaller firms (ETFs) i. While the other parameters are informative in their own right, their main purpose is to obtain better estimates of the spillover coefficients.

The results for the ETFs are presented on the left side of Table 9. Volatility spillovers are positive and significant for SPY to MDY ($a_{35} = 0.044,\ t = 3.831$). Similarly, the spillover from MDY to IWM ($a_{13} = 0.061,\ t = 2.266$) is also significant, and both of these results are consistent with the "large to small" volatility spillover effect. Own-volatility spillovers are positive and statistically significant for SPY. All of the GARCH terms (b_i) are large (> 0.90) and highly significant, and the asymmetric volatility terms (d_i) are positive, significant, and increase monotonically with portfolio size. Thus larger firm portfolios are subject to stronger spikes in volatility given negative returns (the asymmetric volatility effect). The parameter α is positive and significant, indicating that correlations increase when volatility is higher, while the sum of α and β is less than one, which is evidence that conditional correlation is mean-reverting. One anomalous result of this estimation is the negative and significant volatility spillover coefficient from IWM to SPY. Although the coefficient is relatively small (-0.024), negative volatility spillovers are not theoretically possible given the usual assumption that all model parameters are non-negative in the DCC-GARCH specification. However, Conrad and Karanasos (2010) show that "the positive definiteness of the conditional covariance matrix can be guaranteed even if some of the parameters are negative" for time-varying conditional correlation models. We cannot provide an economic rationale for the negative coefficient, but instead view it as a statistical artifact.

The results of the estimations for the size-based CRSP portfolios are contained in the right side of Table 9. The coefficient for volatility spillover from portfolio five to portfolio three is positive and significant ($a_{35} = 0.060, t = 2.016$), indicating the transmission of volatility information from the larger portfolio to the smaller one. The coefficients for asymmetric volatility (d_i) once again increase with the market capitalizations of the stocks included in the portfolios, and the values of the α and β coefficients are similar to those for the ETFs. There are no significant spillovers from either of the larger stock portfolios (Q3 and Q5) to the smallest stock portfolio (Q1). The weaker spillover results may reflect the fact that informed investors may choose to impound their information regarding macroeconomic events or stock market movements by taking positions in the highly liquid ETFs. In addition to their popularity and liquidity, these securities are not subject to the "uptick" rule, providing an additional reason they may be utilized as instruments for informed and/or liquidity traders. The results of prior sections of this paper point to increased efficiency in the return generating process. But even though information regarding returns has become more efficiently impounded into stock prices over the past twenty-five years, volatility spillovers remain persistent and are impounded at longer than intraday horizons. ETFs are easily traded on multiple trading venues in one transaction, as opposed to the multiple and significant number of transactions necessary to replicate trading in the CRSP portfolios. Market-wide common information (or informed trading) may be more readily reflected in in these highly liquid single transaction securities, and there is theoretical and empirical evidence that trading activity itself may induce stock volatility.[8] The issue of potential market volatility induced by ETF trading remains a potentially serious concern, as noted by Bradley and Litan (2010) Chordia, Sarkar, and Subrahmanyam (2011), and the CFTC-SEC Joint Reports (2010a, 2010b).

Implied Volatility Spillovers

In order to further explore the volatility dynamics and arbitrage relationships among the ETFs and related derivative instruments, we analyze daily options implied volatility data. As noted in Section III, we obtain at the money implied volatility estimates for constant thirty day maturity options for each of the ETFs from Bloomberg Professional®. . The data are truncated at the one percent level at each extreme to remove the effects of outliers (n = 1,932). Sample statistics for this data are provided in Table 10. We seek to determine whether there are spillovers of implied volatility among the ETFs, so we conduct Granger causality tests as in Equation (1), but

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[8] See, for example, Avramov, Chordia, and Goyal (2006), French and Roll (1986), Haugen (2010), and Malinova and Park (2011).

substitute estimates of implied variance in place of the return data. Implied variance is obtained simply by squaring our estimates of implied volatility (that are expressed in annual standard deviations).

The results of these tests are contained in Table 11, and are quite similar to the results obtained using the DCC-GARCH(1,1) estimation. Own-spillovers (the coefficients $b_{i,j,s}$ where $i = j$) are strong and significant for all of the joint and sum tests, reflecting the persistence of implied volatility over short periods of time. There are also positive and significant spillovers from SPY to both IWM and MDY for the joint test. The results are economically significant when comparing the levels of the sums of the coefficients. The sum of the spillover coefficients from SPY to IWM is 0.22, which is 28 percent of the sum of own-spillovers (0.78), and this sum is statistically significant at the five percent level. Moreover, the sum of spillovers from SPY to MDY (0.27) reflects 35 percent of MDY own-spillovers (0.78), and this result is statistically significant at the five percent level. According to the sum test, there is no significant spillover from either IWM or MDY to SPY. The volatility of SPY is essentially described by its own past values.

Overall, these results support the earlier finding of positive volatility spillovers from large stock ETFs to smaller ones, and highlight the interrelated nature of these derivative securities. There is active and significant arbitrage activity among the ETFs and their related derivative securities, and volatility spillover information is transmitted not just through ETFs themselves, but also in the options market.

VII. Conclusion

We examine the market efficiency of ETFs and size-based portfolios and find that U.S. equity markets have become significantly more efficient over the past fifty years, especially in the last decade. We confirm the early results of Lo and MacKinlay (1988, 1990) regarding return autocorrelation of large vs. small firm returns, but demonstrate through similar and additional methodologies that these anomalies are currently much less pronounced, if they exist at all. For three high volume, extremely liquid ETFs, there is no positive serial correlation in returns on a daily basis as measured by variance ratios. In fact, there is evidence of negative serial correlation, consistent with the short-term reversal effect of Jegadeesh and Titman (1995). Positive cross- and own-autocorrelation in size-based portfolio returns has been greatly reduced over the past twenty-five years, and prior evidence of this phenomenon may have been induced by asynchronous trading in small stocks. Lead-lag effects between large and small firm portfolios have all but disappeared. We observe negative serial correlation in ETF daily returns during the most recent sample period. However, this phenomenon cannot be attributed to a bid-ask bounce, since we obtain similar results using the midpoint of closing bid and ask quotes.

Volatility continues to "spill over" from large firm portfolios to smaller ones over the past decade, and the volatility spillovers are even more pronounced for size-based ETFs. The observation that negative return shocks lead to higher volatility than do positive return shocks (asymmetric volatility) remains valid, both for portfolios and ETFs of all sizes, and correlations continue to increase during periods of higher volatility. Additionally, volatility spillovers are significant in ETF options markets since implied volatility information is transmitted from SPY to each of the smaller ETFs on a lead-lag basis. The implications of these results are relevant to market practitioners, regulators, and policy makers. Increased market efficiency may be related to the highly efficient institutional structure of U.S. equity markets, although the possibility of potentially destabilizing effects surrounding ETF trading warrants further consideration and study.

References

Avramov, D., T. Chordia, and A. Goyal, 2006, The impact of trades on daily volatility, *Review of Financial Studies* 19, 1241-77.

Badrinath, S. G., J. R. Kale and T. H. Noe, 1995, Of shepherds, sheep, and the cross-autocorrelations in equity Returns, *The Review of Financial Studies* 8, 401-30.

Ben-David, I, F.A. F. Franzoni, and R. Moussawi, 2012, ETFs, arbitrage, and shock propagation. Fisher College of Business Working Paper No. 2011-03-20.

Bradley, H., and R. Litan, 2010, Choking the Recovery: Why new growth companies aren't going public and unrecognized risks of future market disruptions, *Ewing Marion Kauffman Foundation.*

Boudoukh, J., M. P. Richardson and R. E. Whitelaw, 1994, A tale of three schools: Insights on autocorrelations of short-horizon stock returns, *Review of Financial Studies* 7, 539–73.

CFTC-SEC, 2010a, Preliminary findings regarding the market events of May 6, 2010, May 18, 2010.

CFTC-SEC 2010b, Findings regarding the market events of May 6, 2010, September 30, 2010.

Charles, A. and O. Darné, 2009, Variance-ratio tests of random walk: An overview, *Journal of Economic Surveys* 23, 503-27.

Cochrane, J. H., 2008, The dog that did not bark: A defense of return predictability, *The Review of Financial Studies* 21, 1533-75.

Chordia, T., A. Sarkar, and A. Subrahmanyam, 2011, Liquidity dynamics and cross-autocorrelations, *Journal of Financial and Quantitative Analysis* 46, 709-36.

Chung, K. H. and H. Zhang, 2013, A Simple Approximation of Intraday Spreads Using Daily Data, Journal of Financial Markets (forthcoming).

Conrad, C., and M. Karanasos, 2010, Negative volatility spillovers in the unrestricted ECCC-Garch Model, *Econometric Theory* 26, 838-62.

Conrad, J., M. N. Gultekin and G. Kaul, 1991, Asymmetric predictability of conditional variances, *Review of Financial Studies* 4, 597-622.

Conrad, J. and G. Kaul, 1988, Time-variation in expected returns, *Journal of Business* 61, 409-25.

Easley, D., M. de Prado, and M. O'Hara, 2011, The microstructure of the "flash crash": Flow toxicity, liquidity crashes, and the probability of informed trading. *Journal of Portfolio Management* 37, 118-28.

Engle, R., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business & Economic Statistics* 20, 339-50.

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25, 383–417.

Fama, E. F., and K. R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-73.

Fargher, N. L., and R. A. Weigand, 1998, Changes in the stock price reaction of small firms to common information, *Journal of Financial Research* 21, 105-21.

French, K. R., and R. Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17, 5-26.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *The Journal of Finance* 48, 1779-1801.

Goyal, A., and P. Santa-Clara, 2003. Idiosyncratic risk matters!, *The Journal of Finance* 58, 975-1007.

Griffin, J. M., P. J. Kelly, and F. Nardari, 2010, Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets, *Review of Financial Studies* 23, 3225-77.

Haugen, R.A., 2010, The new finance: Overreaction, complexity and uniqueness (4th ed.). (Prentice Hall, Upper Saddle River, NJ).

Henry, Ó. T., and J. Sharma, 1999, Asymmetric conditional volatility and firm size: Evidence from australian equity portfolios, *Australian Economic Papers* 38, 393-406.

Hibbert, A. M., R. T. Daigler, and B. Dupoyet, 2008, A behavioral explanation for the negative asymmetric return–volatility relation, *Journal of Banking & Finance* 32, 2254-66.

Hoque, H. A. A. B., J. H. Kim, and C. S. Pyun, 2007, A comparison of variance ratio tests of random walk: A case of Asian emerging stock markets, *International Review of Economics & Finance* 16, 488-502.

Hou, K., 2007, Industry information diffusion and the lead-lag effect in stock returns, *The Review of Financial Studies* 20, 1113-38.

Jegadeesh, N., and S. Titman, 1995, Short-horizon return reversals and the bid-ask spread, *Journal of Financial Intermediation* 4, 116-32.

Jensen, M. C., 1978, Some anomalous evidence regarding market efficiency, *Journal of Financial Economics* 6, 95-101

Keim, D. B., and R. F. Stambaugh, 1986, Predicting returns in the stock and bond maricets, *Journal of Financial Economics* 17, 357-90.

Llorente, G., R. Michaely, G. Saar, and J. Wang, 2002, Dynamic volume-return relation of individual stocks, *The Review of Financial Studies* 15, 1005-47.

Lo, A., and A. C. MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification Test, *Review of Financial Studies* 1, 41-66.

Lo, A. W., and A. C. MacKinlay, 1990, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181-211.

Malinova, K., and A. Park, 2011, Trading volume in dealer markets, *Journal of Financial and Quantitative Analysis* 45, 1447-84.

Mech, T. S., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307-44.

O'Hara, M., and M. Ye, 2011, Is market fragmentation harming market quality?, *Journal of Financial Economics* 100, 459-74.

Orskaug, E., 2009, Multivariate DCC-GARCH model - with various error distributions, Norwegian Computing Center Working Paper.

Saffi, P. A. C., and K. Sigurdsson, 2011, Price efficiency and short selling, *Review of Financial Studies* 24, 821-852.

Wright, J. H., 2000, Alternative variance-ratio tests using ranks and signs, *Journal of Business & Economic Statistics* 18, 1-9.

Wurgler, J. A., 2011, On the economic consequences of index-linked investing, in G. Rosenfeld, J.W. Lorsch, and R. Khurana, eds.: Challenges to Business in the Twenty-First Century. (American Academy of Arts and Sciences, Cambridge, MA).

Table 1. Summary Statistics and Correlation Matrix for Weekly ETF Returns.

Jun 1, 2000 – Sep 26, 2012, n = 638

Panel A: Sample Statistics .

ETF	Mean	Std Dev	Skew.	Kurt.
IWM	0.111	1.298	-0.809	4.260
MDY	0.131	1.188	-0.974	5.399
SPY	0.036	1.025	-0.803	5.395

Panel B: Correlation Matrix for ETFs and CRSP Quintiles.

	IWM	MDY	SPY	Q1	Q3	Q5
IWM	1.000					
MDY	0.963	1.000				
SPY	0.917	0.951	1.000			
Q1	0.871	0.825	0.799	1.000		
Q3	0.959	0.954	0.928	0.919	1.000	
Q5	0.910	0.947	0.971	0.904	0.984	1.000

Panel A contains sample statistics for weekly returns for three size-based ETFs that track the Russell 2000 Small Cap Index (IWM), the S&P 400 MidCap Index (MDY), and the S&P 500 Index (SPY), obtained from Bloomberg Professional®. Daily data for the 4:00PM ET closing price is converted to weekly returns on a Wednesday to Wednesday basis. Panel B contains correlation coefficients for the returns of the ETFs and three size-based CRSP portfolios, computed in the identical manner. The CRSP portfolio data is obtained from the website of Dr. Kenneth French.

Table 2. Summary Statistics and Correlation Matrices for Weekly Returns of CRSP portfolio Size Quintiles.

Panel A: Sample Statistics

Sep 6, 1962 -Sep 26, 2012, n = 2,612

Quintile	Mean	Std Dev	Skew.	Kurt.
Q1	0.443	2.280	-0.676	9.524
Q3	0.242	2.626	-0.762	9.756
Q5	0.231	2.543	-0.746	9.350

Sep 6, 1962 - Dec 26, 1985, n = 1,216

Quintile	Mean	Std Dev	Skew.	Kurt.
Q1	0.365	2.220	-0.026	5.618
Q3	0.281	2.230	-0.145	4.458
Q5	0.254	2.114	-0.154	4.239

Jan 1, 1986 – May 31, 2000 n = 753

Quintile	Mean	Std Dev	Skew.	Kurt.
Q1	0.635	2.053	-1.513	17.423
Q3	0.239	2.483	-1.378	14.244
Q5	0.242	2.566	-1.198	12.284

Jun 1, 2000 – Sep 26, 2012, n = 638

Quintile	Mean	Std Dev	Skew.	Kurt.
Q1	0.344	2.653	-0.851	8.924
Q3	0.164	3.444	-0.671	7.682
Q5	0.166	3.231	-0.674	7.600

Panel B: Correlation Matrices

Sep 6, 1962 -Sep 26, 2012, n = 2,612

Quintile	Q1	Q3	Q5
Q1	1.000		
Q3	0.911	1.000	
Q5	0.870	0.979	1.000

Sep 6, 1962 - Dec 26, 1985, n = 1,216

Quintile	Q1	Q3	Q5
Q1	1.000		
Q3	0.937	1.000	
Q5	0.896	0.980	1.000

Jan 1, 1986 – May 31, 2000 n = 753

Quintile	Q1	Q3	Q5
Q1	1.000		
Q3	0.889	1.000	
Q5	0.824	0.973	1.000

Jun 1, 2000 – Sep 26, 2012, n = 638

Quintile	Q1	Q3	Q5
Q1	1.000		
Q3	0.919	1.000	
Q5	0.904	0.984	1.000

This table contains descriptive statistics for weekly percentage returns on three size-based CRSP portfolios, obtained from the website of Dr. Kenneth French. The quintiles are constructed using market capitalization as of June each year using NYSE breakpoints. Daily return data for NYSE/AMEX/NASDAQ firms is converted to weekly returns on a Wednesday to Wednesday basis.

Table 3. Weekly Variance Ratios and Tests Statistics of Exchange Traded Funds.

Jun 1, 2000 – Sep 26, 2012, n = 638

q	VR	*z-stat*	VR	*z-stat*	VR	*z-stat*
2	0.94	(-1.05)	0.94	(-0.86)	0.94	(-0.95)
4	0.95	(-0.52)	0.94	(-0.51)	0.90	(-0.88)
8	0.97	(-0.21)	0.98	(-0.10)	0.95	(-0.31)
16	0.95	(-0.22)	1.00	(-0.02)	0.98	(-0.09)

This table contains variance ratios and heteroskedasticity robust test statistics (in parentheses) for the three ETFs under study. Variance ratios (VR) greater than one imply serial correlation and hence predictability. Numbers in parentheses are heteroskedasticity-consistent z-statistics for tests examining whether the variance ratios equal one. *q* is the number of weekly observations aggregated to form the variance ratios. ***Significant at the 1% level, **Significant at the 5% level.

Table 4. Weekly Variance Ratios and Test Statistics of CRSP Portfolios.

Panel A: Sep 6, 1962 - Dec 26, 1985, n = 1,216

	Q1			Q3			Q5		
q	VR	*z-stat*		VR	*z-stat*		VR	*z-stat*	
2	1.38	(8.85)	***	1.25	(6.65)	***	1.09	(2.57)	***
4	1.87	(11.26)	***	1.52	(7.55)	***	1.18	(2.66)	***
8	2.38	(11.82)	***	1.74	(6.98)	***	1.24	(2.25)	**
16	2.68	(10.24)	***	1.82	(5.37)	***	1.22	(1.36)	

Panel B: Jan 1, 1986 – May 31, 2000 n = 753

2	1.38	(3.21)	***	1.13	(1.24)		0.99	(-0.11)	
4	1.82	(4.30)	***	1.17	(1.02)		0.97	(-0.28)	
8	2.42	(5.89)	***	1.27	(1.22)		0.94	(-0.37)	
16	2.76	(5.93)	***	1.26	(0.95)		0.89	(-0.51)	

Panel C: Jun 1, 2000 – Sep 26, 2012, n = 638

2	1.17	(2.74)	***	0.99	(-0.13)		0.94	(-0.89)	
4	1.41	(3.70)	***	1.05	(0.45)		0.92	(-0.69)	
8	1.61	(3.57)	***	1.07	(0.43)		0.95	(-0.25)	
16	1.78	(3.17)	***	0.98	(-0.08)		0.93	(-0.25)	

This table contains variance ratios and heteroskedasticity robust test statistics for three size based CRSP Portfolios for three separate time periods. Variance ratios (VR) greater than one imply serial correlation and hence predictability. The numbers in parentheses are heteroskedasticity-consistent *z-stat*istics for tests examining whether the variance ratios equal one. *q* is the number of weekly observations aggregated to form the variance ratios. ***Significant at the 1% level, **Significant at the 5% level.

Table 5. Daily Variance Ratio Tests, 2000 – 2012.

	IWM			MDY			SPY				Q1			Q3		Q5		
q	VR	*z-stat*		VR	*z-stat*		VR	*z-stat*		*q*	VR	*z-stat*		VR	*z-stat*	VR	*z-stat*	
Lo and MacKinlay (1988) Variance Ratios																		
2	0.93	(-2.54)	**	0.96	(-1.27)		0.93	(-2.31)	**	2	1.11	(3.43)	***	1.00	(0.13)	0.96	(-1.34)	
5	0.86	(-2.14)	**	0.88	(-1.62)		0.82	(-2.35)	**	5	1.40	(5.43)	***	0.99	(-0.15)	0.88	(-1.56)	
10	0.78	(-2.13)	**	0.78	(-1.78)		0.74	(-2.11)	**	10	1.62	(5.44)	***	0.95	(-0.43)	0.81	(-1.57)	
20	0.79	(-1.43)		0.79	(-1.19)		0.73	(-1.50)		20	1.93	(5.66)	***	1.01	(0.04)	0.81	(-1.09)	
Wright (2000) Ranks Test																		
2	0.96	(-1.96)	**	1.00	(0.11)		0.95	(-2.51)	**	2	1.15	(8.28)	***	1.03	(1.89)	0.99	(-0.66)	
5	0.91	(-2.35)	**	0.95	(-1.34)		0.88	(-2.97)	***	5	1.49	(12.35)	***	1.05	(1.30)	0.94	(-1.44)	
10	0.83	(-2.85)	***	0.84	(-2.60)	**	0.79	(-3.40)	***	10	1.79	(13.06)	***	1.03	(0.47)	0.87	(-2.06)	**
20	0.83	(-1.88)	**	0.82	(-1.99)	**	0.75	(-2.77)	***	20	2.20	(13.40)	***	1.10	(1.14)	0.87	(-1.45)	
Wright (2000) Rank Scores Test																		
2	0.95	(-3.02)	***	0.98	(-0.90)		0.95	(-3.04)	***	2	1.14	(7.57)	***	1.02	(1.28)	0.98	(-1.07)	
5	0.88	(-3.07)	***	0.92	(-2.02)	**	0.87	(-3.33)	***	5	1.46	(11.64)	***	1.03	(0.79)	0.94	(-1.65)	
10	0.79	(-3.47)	***	0.81	(-3.07)	***	0.78	(-3.56)	***	10	1.72	(11.94)	***	0.99	(-0.08)	0.86	(-2.31)	**
20	0.78	(-2.44)	**	0.80	(-2.28)	**	0.75	(-2.79)	***	20	2.08	(12.07)	***	1.05	(0.51)	0.85	(-1.72)	

This table contains daily variance ratios and *z(*)q* test statistics for the ETFs and three size based CRSP portfolios. Variance ratios greater than one imply serial correlation and hence predictability. The numbers in parentheses are heteroskedasticity-consistent *z-stat*istics for tests examining whether the variance ratios equal one. The Wright (2000) statistics test the same hypothesis using ranks and rank scores of the data in the Lo and Mackinlay (1988) specification. ***Significant at the 1% level, **Significant at the 5% level.

Table 6. Daily Variance Ratio Tests, 2000 – 2012. Data are closing bid/ask midpoints for the ETFs and value-weighted returns for the CRSP Quintiles.

	IWM			MDY			SPY				Q1			Q3			Q5		
q	VR	z-stat		VR	z-stat		VR	z-stat		*q*	VR	z-stat		VR	z-stat		VR	z-stat	
Lo and MacKinlay (1988) Variance Ratios																			
2	0.92	(-2.58)	***	0.92	(-1.95)		0.92	(-2.48)	**	2	0.96	(-1.38)		0.99	(-0.46)		0.91	(-2.85)	***
5	0.84	(-2.32)	**	0.77	(-2.55)	**	0.81	(-2.45)	**	5	0.98	(-0.23)		0.94	(-0.92)		0.81	(-2.55)	**
10	0.76	(-2.33)	**	0.68	(-2.35)	**	0.73	(-2.25)	**	10	0.99	(-0.14)		0.86	(-1.39)		0.73	(-2.38)	**
20	0.71	(-1.90)	**	0.67	(-1.62)		0.71	(-1.65)		20	1.06	(0.40)		0.87	(-0.90)		0.70	(-1.75)	**
Wright (2000) Ranks Test																			
2	0.96	(-2.15)	**	1.00	(-0.07)		0.95	(-2.63)	***	2	1.02	(1.12)		1.02	(1.16)		0.93	(-3.70)	***
5	0.91	(-2.28)	**	0.94	(-1.42)		0.88	(-3.09)	***	5	1.10	(2.63)	***	1.00	(0.05)		0.86	(-3.53)	***
10	0.83	(-2.81)	***	0.86	(-2.34)	**	0.79	(-3.43)	***	10	1.15	(2.47)	***	0.94	(-0.95)		0.79	(-3.54)	***
20	0.81	(-2.08)	**	0.84	(-1.79)		0.74	(-2.91)	***	20	1.28	(3.19)	***	0.97	(-0.39)		0.77	(-2.59)	***
Wright (2000) Rank Scores Test																			
2	0.95	(-3.02)	***	0.98	(-0.94)		-0.94	(-3.24)	***	2	0.99	(-0.33)		1.01	(0.36)		0.93	(-4.02)	***
5	0.88	(-2.98)	***	0.90	(-2.43)	**	-0.86	(-3.44)	***	5	1.05	(1.23)		0.98	(-0.60)		0.85	(-3.70)	***
10	0.79	(-3.39)	***	0.81	(-3.08)	***	-0.78	(-3.64)	***	10	1.06	(1.07)		0.90	(-1.68)		0.77	(-3.77)	***
20	0.76	(-2.73)	***	0.80	(-2.20)	**	-0.74	(-2.91)	***	20	1.16	(1.76)		0.90	(-1.12)		0.75	(-2.83)	***

This table contains daily variance ratios and *z(*)q* test statistics for the ETFs and three size based CRSP portfolios. In contrast to Table 5, the data for these ratios are closing bid/ask midpoints for the ETFs, and value-weighted returns for the CRSP Quintiles. Variance ratios greater than one imply serial correlation and hence predictability. The numbers in parentheses are heteroskedasticity-consistent *z-stat*istics for tests examining whether the variance ratios equal one. The Wright (2000) statistics test the same hypothesis using ranks and rank scores of the data in the Lo and Mackinlay (1988) specification. ***Significant at the 1% level, **Significant at the 5% level.

Table 7. Weekly Autocorrelation Matrix for ETFs and CRSP Portfolios

Panel A: ETFs, June 1, 2000 – Sep 26, 2012, n = 643

	IWM_t	MDY_t	SPY_t
IWM_{t-1}	-0.075	-0.036	-0.045
MDY_{t-1}	-0.066	-0.041	-0.040
SPY_{t-1}	-0.082	-0.055	-0.071

Panel B: CRSP Quintiles, June 1, 2000 – Sep 26, 2012, n = 643

	$Q1_t$	$Q3_t$	$Q5_t$
$Q1_{t-1}$	0.127	-0.052	-0.065
$Q3_{t-1}$	0.130	-0.040	-0.050
$Q5_{t-1}$	0.147	-0.018	-0.030

Panel C: CRSP Quintiles, Jan 1, 1986 – May 31, 2000 n = 753

	$Q1_t$	$Q3_t$	$Q5_t$
$Q1_{t-1}$	0.391	0.148	0.079
$Q3_{t-1}$	0.365	0.179	0.108
$Q5_{t-1}$	0.354	0.194	0.122

Panel D: CRSP Quintiles, Sep 6, 1962 - Dec 26, 1985, n = 1,216

	$Q1_t$	$Q3_t$	$Q5_t$
Q1t-1	0.376	0.244	0.202
Q3t-1	0.381	0.278	0.241
Q5t-1	0.369	0.279	0.243

This table presents autocorrelations among the weekly returns of the ETFs and size-based portfolios and one lag of those same returns. The table is comparable to Table 4 of Lo and MacKinlay (1990). The magnitudes of these autocorrelations are slightly higher than theirs for the earliest period, mostly due to the inclusion of NASDAQ firms in our sample. The figures below the diagonal are generally larger than those above, demonstrating that information from lagged returns flows in general from larger to smaller firms.

Table 8. Daily Granger Causality in ETFs and CRSP Portfolios.

Panel A: ETFs

Joint Test	Dependent Variable, Chi Square (5) Statistics		
	IWM	MDY	SPY
$b_{i,1,s}$	3.57	1.87	3.93
$b_{i,3,s}$	6.98	5.12	8.98
$b_{i,5,s}$	4.81	4.31	7.66

Sum Test	Sum of Lag Coefficients and t-statistics					
	IWM		MDY		SPY	
	Sum	*t*	Sum	*t*	Sum	*t*
$\Sigma b_{i,1,s}$	-0.21	-0.92	0.15	0.64	0.04	0.18
$\Sigma b_{i,3,s}$	0.12	0.32	-0.37	-1.00	0.04	0.13
$\Sigma b_{i,5,s}$	-0.08	-0.33	0.04	0.15	-0.29	-1.25

Panel B: CRSP Quintiles

Joint Test	Dependent Variable, Chi Square (5) Statistics		
	Q1	Q3	Q5
$b_{i,1,s}$	6.96	4.18	3.88
$b_{i,3,s}$	5.86	5.41	4.77
$b_{i,5,s}$	8.09	7.55	8.97

Sum Test	Sum of Lag Coefficients and t-statistics					
	Q1		Q3		Q5	
	Sum	*t*	Sum	*t*	Sum	*t*
$\Sigma b_{i,1,s}$	0.21	1.33	-0.13	-0.59	-0.02	-0.12
$\Sigma b_{i,3,s}$	0.06	0.27	0.19	0.58	0.21	0.68
$\Sigma b_{i,5,s}$	-0.11	-0.44	-0.25	-0.75	-0.44	-1.35

This table presents results for the weekly Granger-causality tests of returns of the three CRSP portfolios. The coefficients $b_{i,j,s}$ represent five lags of each portfolio's daily returns. The null hypothesis for the Joint test is that all the coefficients are jointly equal to zero, while the null hypothesis for the Sum test is that the sum of the coefficients is zero. ***Significant at the 1% level, **Significant at the 5% level.

Table 9. Volatility Spillovers – Estimation Results of DCC MV-GARCH(1,1)-t Model for the CRSP Portfolios and ETFs, Jun 1, 2000 – Sep 26, 2012.

	ETFs			**CRSP Quintiles**		
Coefficient	Value	*t-stat*		Value	*t-stat*	
c_1	<0.001	6.289	***	<0.001	5.765	***
c_2	<0.001	6.571	***	<0.001	5.140	***
c_3	<0.001	7.065	***	<0.001	5.199	***
a_{11}	-0.011	-0.541		0.008	5.980	***
a_{13}	0.061	2.266	**	0.010	-0.286	
a_{15}	0.012	0.859		0.030	0.728	
a_{31}	-0.015	-1.128		0.007	-0.548	
a_{33}	0.022	0.762		-0.023	2.004	**
a_{35}	0.044	3.831	**	0.060	2.016	**
a_{51}	-0.024	-2.800	***	-0.018	-1.799	
a_{53}	0.012	1.319		0.000	0.964	
a_{55}	0.035	2.746	***	0.045	1.371	
b_1	0.916	121.520	***	0.910	128.178	***
b_2	0.924	150.615	***	0.916	146.497	***
b_3	0.932	164.044	***	0.918	156.614	***
d_1	0.036	4.636	***	0.061	2.226	**
d_2	0.042	5.754	***	0.063	5.092	***
d_3	0.073	9.088	***	0.087	9.115	***
α	0.031	9.836	***	0.033	10.337	***
β	0.963	216.866	***	0.956	183.050	***
ν	16.531	9.064	***	13.392	10.554	***
Observations		3,103			3,103	
Quasi-Log Likelihood		35,636			34,665	

This table contains of the estimation of a DCC MV-GARCH(1,1)-t Model for the ETFs and the CRSP portfolios. The coefficients a_{ij} (where $i < j$) are of particular interest since they indicate volatility spillover from the larger ETF or portfolio j to the smaller ETF or portfolio i. The estimations contain a constant term c_{ii}, a GARCH term b_i, as well as a dummy variable coefficient (d_i) for asymmetric volatility as suggested by Glosten, Jagannathan, and Runkle (1993). The equation estimating conditional correlation contains the parameters α_i and β_i which represent the relationship between conditional correlation and lagged volatility, and a decay factor. The Student-t parameter for shape (ν) is included in the maximum likelihood estimation. ***Significant at the 1% level, **Significant at the 5% level.

Table 10. Summary Statistics for Daily ETF Implied Volatility.

Jan 10, 2005 – Sep 26, 2012, n = 1,932

ETF	Mean	Std Dev	Skew.	Kurt.
IWM	0.267	0.104	1.827	3.951
MDY	0.230	0.104	1.900	4.380
SPY	0.195	0.098	1.958	4.853

This table contains sample statistics for daily implied volatility estimates for three size-based ETFs that track the Russell 2000 Small Cap Index (IWM), the S&P 400 MidCap Index (MDY), and the S&P 500 Index (SPY). The implied volatility estimates are for "at the money" options with constant thirty day maturities, obtained from Bloomberg®. The data are truncated at the one percent level at each extreme to remove the effects of outliers (n = 1,932).

Table 11. Implied Volatility Spillovers.

Joint Test — Dependent Variable, Chi Square (5) Statistics

	IWM		MDY		SPY	
$b_{i,1,s}$	175.00	***	9.64		11.61	**
$b_{i,3,s}$	5.10		81.18	***	3.31	
$b_{i,5,s}$	7.03	**	19.94	***	271.41	***

Sum Test — Sum of Lag Coefficients and *t*-statistics

	IWM			MDY			SPY		
	Sum	*t-stat*		Sum	*t-stat*		Sum	*t-stat*	
$\Sigma b_{i,1,s}$	0.78	11.40	***	-0.01	0.75		-0.10	-1.86	
$\Sigma b_{i,3,s}$	0.06	0.61		0.78	8.65	***	0.00	0.01	
$\Sigma b_{i,5,s}$	0.22	2.02	**	0.27	3.10	***	1.12	12.21	***

This table contains the results of Granger causality tests as in Equation (2), but the raw data for the tests are implied volatility estimates obtained from Bloomberg® from January 10, 2005 to September 26, 2012. The data are truncated at the one percent level at each extreme to remove the effects of outliers (n = 1,932). The implied volatility estimates are for "at-the-money" options with constant thirty day maturities for each of the ETFs in the study. We square the implied volatility data to obtain estimates of implied variance, which is used in the Granger causality estimations. ***Significant at the 1% level, **Significant at the 5% level.