TEMPORARY COMPONENTS OF STOCK PRICES: A SKEPTIC'S VIEW

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Abstract

Recent empirical work has uncovered U-shaped patterns of large magnitude in the serial correlation estimates of multi-year stock returns. The current literature in finance has taken this evidence to mean that there exists a temporary component of stock prices. This paper provides an alternative explanation regarding these findings. Specifically, we show that the patterns in serial correlation estimates and their magnitude observed in previous studies should be expected under the null hypothesis of serial independence.

Key words: autocorrelation, temporary component, joint test.

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1 Introduction

Researchers have reported seemingly striking evidence of stock return predictability over long return horizons, which has led many to question the descriptive power of the random walk hypothesis. Much of this evidence regarding the predictability of long term returns has been presented in terms of correlation or variance patterns over the different return horizons. Although the discussion we give herein applies to many of the papers in the recent literature, we consider the heavily cited paper by Fama and French (1988) as a representative sample of this evidence. (In addition, see the original work by Stambaugh (1986) and later studies in finance and macroeconomics by Campbell and Mankiw (1987), Huizinga (1987), Poterba and Summers (1988), Lo and Mackinlay (1988) and Cochrane (1988), among others).

For example, Fama and French (1988) report multiperiod autocorrelations for a variety of industry, size and index portfolios. As an illustration, consider the NYSE equal weighted stock index of returns. The serial correlation pattern for this portfolio is -5%,-22%,-32%,-36%,-34%,-13%,8% and 22% for the 1-6,8 and 10 year returns, respectively. The magnitude of the largest of these correlations (i.e. -36%) is considerably higher than previously believed, suggesting greater predictability in stock returns. Furthermore, the U-shaped pattern in the coefficient estimates suggests rejecting the random walk model in favor of a model which incorporates a large mean reverting component as well as a permanent component to stock prices.

However, the magnitude and patterns in these serial correlation estimates are the type of results we should expect to see generated from a random walk model. This is due to the combination of two effects. First, over the vector of multiperiod autocorrelation estimates, some of the estimates will differ from their random-walk expected value of zero. Order statistic theory suggests these differences can be quite large. Second, autocorrelations of similar holding period returns are highly correlated. These autocorrelations will therefore pick-up similar variation, irrespective of whether it is real or spurious. These effects induce U-shaped or humped shape patterns around the largest estimates — the same pattern found in actual stock return data. Of particular interest, this alternative explanation for the U-shaped pattern in the observed serial correlation estimates relies on the random walk being the true model.

This paper is presented as follows. Section 2 gives our alternative interpretation of the much cited long-horizon serial correlation in stock returns. In Section 3, we investigate further the intertemporal behavior of long-horizon returns by examining some implications of the joint properties of multiperiod autocorrelations. Section 4 concludes.

2 A Skeptic's View

2.1 On the Existing Evidence

Fama and French (1988) collect monthly data on continuously compounded real stock returns from 1926-1985 and estimate 1,2,...,6,8 and 10 year autocorrelations (denote $\hat{\beta}_j$, where j is the period length). Table 1 summarizes these bias-adjusted autocorrelation estimates. At first glance, the results appear quite striking. In particular, $\hat{\beta}_j$ ranges from -25% to -45% at $j = 36 - 60$ months. This is considerably different from the random walk's implied average value of $\hat{\beta}_j$ equal to zero. (For similar results in a related context, see also Poterba and Summers (1988)).

In addition, there is other evidence of predictable components in stock returns. Lo and MacKinlay (1988) and Conrad and Kaul (1988,1989) document significant positive autocorrelation at very short horizons; however, much of the focus on this evidence has concentrated on market microstructure effects and seems to have little implication for long horizon returns. In extensions to multivariate frameworks, Gibbons and Ferson (1983), Keim and Stambaugh (1986), and Fama and French (1988b), among others, find significant evidence of time-varying expected returns over different horizons. Based on this evidence, the implications for whether a temporary component exists and for whether stock returns are negatively correlated at long horizons, however, is less clear (see Hodrick (1992)).

With respect to the long-horizon autocorrelations, recent work questions the reliability of the individual point estimates (see, for example, Richardson and Stock (1989) and Kim, Nelson and Startz (1991)). The overall conclusion from this work is that long-horizon t-statistics tend to overstate the degree of mean-reversion in the data. However, the analysis in these papers provide only a cursory treatment of the joint behavior of the multiperiod autocorrelations. Prior to the long-horizon autocorrelation evidence, the prevailing view in finance was that long-term stock returns were uncorrelated. Under this model, what magnitude and pattern in the serial correlation estimates should we expect to find across the different multiperiods?

2.2 Magnitude of the Estimates

In order to reexamine the long horizon autocorrelation evidence, we investigate the implied behavior of the autocorrelation estimates via monte carlo simulation. Specifically, we look at two types of simulations, in which we draw 720 observations from either a $N(\mu, \sigma^2)$ distribution (in which the μ and σ match the sample estimates of the index returns) or from the sample distributions of actual portfolio returns with replacement. We then calculate the multiperiod autocorrelation for periods of length $12, 24, \ldots, 72, 96$ and 120. To coincide with the existing literature, these estimates are then adjusted for small sample bias. This procedure is repeated 5000 times for each simulation. Note that the results were robust to the two simulation methods.

From the theory of order statistics we should expect that, across the different periods j, some of the $\hat{\beta}_j$ to be different from their individual expected value of zero. In Table 2, we report the monte carlo estimate of the empirical distribution of $\hat{\beta}_{j^*}$, where j^* is the period in which the largest absolute deviation from zero occurs ($j \in \{12, 24, \ldots, 72, 96, 120\}$). As intuition suggests, the distribution of $\hat{\beta}_{j^*}$ is considerably removed from the distribution we would expect from the individual $\hat{\beta}_j$'s. Moreover, over the 5000 replications, the average of the absolute value of $\hat{\beta}_{j^*}$ is .353, which interestingly enough is in the middle of the range of the actual multiperiod autocorrelations. As an additional measure, the last two columns of Table 3 provide $|\hat{\beta}_{j^*}|$ and their corresponding monte carlo p-values from observed data on the various portfolios. Most of the statistics are insignificant; for example, over the 29 portfolios, the average p-value is .41.

With respect to the actual estimated multiperiod autocorrelations, however, most of the largest deviations occur in the 36-60 months range. For the simulated data, $\hat{\beta}_{j^*}$ occurs in the 3-5 year range in 26.2% of the 5000 replications. The estimate of the empirical distribution of $\hat{\beta}_{j^*}$ (when $j^* \in \{36, 48, 60\}$) is also given in Table 2. In the relevant negative range of the empirical distribution, the 41% and 5% p-values are -.20 and -.47, respectively. It is interesting to note that in the actual data only a few of the serial correlation estimates in the 3-5 year range lie outside this region (see Table 1). Therefore, even when we condition ex-post on $j^* \in \{36, 48, 60\}$, at a 10% level two-sided test, there is no evidence against the random walk model. Moreover, the average average absolute value of $\hat{\beta}_{j^*}$ (when $j^* \in \{36, 48, 60\}$) is approximately .301, which again is in the appropriate range of actual multiperiod autocorrelation values.

2.3 U-Shaped Pattern in the Estimates

Above, we provided simulation evidence which suggests that departures from the random walk model are similar in magnitude to those of the observed data. Specifically, on average, the absolute value of $\hat{\beta}_{j^*}$ will equal .35. Although this may explain the magnitude of the coefficient estimates, it does not provide an explanation for the well-documented U-shaped pattern in the autocorrelation estimates. However, conditional on $\hat{\beta}_{j^*}$, what pattern should we expect to emerge?

Two counteracting effects provide a possible answer to this question. Due to the fact that the multiperiod autocorrelation estimators have many sample autocovariances in common, the first effect forces surrounding estimators of $\hat{\beta}_{j^*}$ (i.e. $\hat{\beta}_{j^*-1}, \hat{\beta}_{j^*+1}, \hat{\beta}_{j^*-2}, \hat{\beta}_{j^*+2}, \ldots$ et cetera) to have similar point estimates. For example, under the random walk null, it is possible to show that the asymptotic correlation between $\hat{\beta}_{48}$ and $\hat{\beta}_{60}$ is .92 (see Section 3). This implies that over 80% of the variation in $\hat{\beta}_{48}$ can be explained by $\hat{\beta}_{60}$. If $\hat{\beta}_{48} = \hat{\beta}_{j^*}$, then $\hat{\beta}_{60}$ would, therefore, pick-up much of the same spurious serial correlation.

On the other hand, the adjusted estimator $\hat{\beta}_j$ is on average approximately zero. Therefore, a second effect pushes the estimator $\hat{\beta}_j$ towards a point estimate of zero. Intuitively, the effect which dominates depends on how close j is to j^*. For values of j close to j^*, $\hat{\beta}_j$ and $\hat{\beta}_{j^*}$ are essentially the same estimator. Conditional on $\hat{\beta}_{j^*}$, the expectation of $\hat{\beta}_j$ will be slightly smaller than $\hat{\beta}_{j^*}$. For values of j far from j^*, $\hat{\beta}_j$ and $\hat{\beta}_{j^*}$ have very little in common. In this case, the expectation of $\hat{\beta}_j$ will be close to its unconditional average of zero. These two effects then combine to create, on average, either U-shaped or humped shape patterns in the estimates around $\hat{\beta}_{j^*}$.

The above results are good news for financial economists with "random walk priors". In particular, we have provided a natural interpretation of the U-shaped pattern in serial correlation estimators which relies on the random walk model being the true model of stock prices. Not that there will, on average, always be "seemingly" large deviations from the random walk model with smooth patterns in the serial correlation estimates. Without strong a priori suspicions regarding alternative hypotheses, therefore, the current literature's interpretation of the serial correlation estimates is suspect. In contrast to the mean reversion hypothesis, under the serial independence assumption there is no reason to expect U-shaped patterns over humped shape patterns in the serial correlation estimates. If stock returns are independent, then we should expect there to be no relation between serial correlation patterns in different samples. As a matter of fact, this seems to be the case (see Kim, Nelson, and Startz (1991) for a detailed analysis of this point). For example, when comparing the 1926-55 and 1956-85 periods; the serial correlation pattern changes from one of U-shaped to humped shape for all the 10 size sorted portfolios. Consider a representative portfolio, the sixth size decile portfolio: its serial correlation patterns are [-.01%,-.15%,-.38%,-.40%,-.35%,.02%] and [-.07%,-.11%,.11%,.13%,-.07%,-.33%] for 1-6 year holding period returns over the 1926-55 and 1956-85 periods, respectively. Of course, these conclusions are especially subject to small sample considerations. For example, at the 6-year horizon, we only have 5 nonoverlapping observations. Nevertheless, the results are indicative of random walk like behavior in stock prices.

3 Joint Properties of Returns

Most applications of the serial correlation evidence involve interpreting the autocorrelation estimates separately. (For some exceptions, see Richardson (1988), Richardson and Stock (1989), Nelson, Kim and Startz (1991), Daniels and Torous (1991) and McQueen (1992)).

Under the null hypothesis that stock returns are uncorrelated and under some assumptions restricting conditional heteroskedasticity, Richardson and Smith (1989) derive the variance-covariance matrix of serial correlation estimators (such as multiperiod autocorrelations and variance ratios). With respect to the multiperiod autocorrelation estimators $\hat{\beta}_j$, the typical elements of the asymptotic variance-covariance matrix between any two estimators is

$$var\begin{pmatrix}\hat{\beta}_j\\ \hat{\beta}_k\end{pmatrix} = \begin{pmatrix}\frac{2j^2+1}{3j} & \frac{s(j,k)+j^2}{jk}\\ \frac{s(j,k)+j^2}{jk} & \frac{2k^2+1}{3k}\end{pmatrix}$$

$$\text{where} \qquad s(j,k) = 2\sum_{l=1}^{j-1}\left[(j-l)min(j,k-l)\right].$$

In terms of a joint test of the individual t-statistics, a natural ex-ante statistic in finance has been the Wald statistic for a joint test of $\beta_j = 0\ \forall\ j$:

$$J_T(\hat{\beta}) = (\sqrt{T_j}\hat{\beta}_j \quad \dots \quad \sqrt{T_k}\hat{\beta}_k)\left[var\begin{pmatrix}\hat{\beta}_j\\ \vdots\\ \hat{\beta}_k\end{pmatrix}\right]^{-1}\begin{pmatrix}\sqrt{T_j}\hat{\beta}_j\\ \vdots\\ \sqrt{T_k}\hat{\beta}_k\end{pmatrix}\overset{asy}{\sim}\chi^2_8, \qquad (1)$$

where T_j is the number of observations used in estimating β_j.

Richardson and Stock (1991) provide an alternative interpretation of this statistic under a different asymptotic theory (i.e. one in which $\frac{J}{T}\rightarrow\delta$, $0<\delta<1$). In their framework,

J_T's distribution is not χ^2, but instead has a representation in terms of a functional of Brownian motion. Under weak assumptions (including various forms of heteroskedasticity), its representation does not depend on any unknown parameters (i.e. only δ is important). Hence, its asymptotic distribution can be readily approximated via monte carlo simulation. In terms of interpreting the results in this paper, the Richardson-Stock theory provides an asymptotic justification for using the monte carlo p-values given in Tables 2-5. As an aside, results in Richardson and Stock (1989) suggest that this alternative asymptotic theory provides a better approximation in small samples.

3.1 Joint Tests: Empirical Results

3.1.1 Multiperiod Autocorrelations

We calculate the $J_T(\hat{\beta})$ statistic for the 17 industry, 10 size and 2 index portfolios looked at in Fama and French (1988). A description of the data is provided in Fama and French (1988). In brief, they look at autocorrelation patterns in 1-6,8, and 10 year holding period returns for various portfolios from 1926-1985. To coincide with the simulation, we use the bias adjusted slopes given in Table 1.

The test results are provided in Table 3. The zero autocorrelation model can be rejected for only one portfolio (i.e. utilities) at the 1% table value. Four other portfolios approximate the 5% table value. Given the divergence between $\hat{\beta}_j$'s asymptotic and small sample distribution reported in the literature, one might expect there to be a similar divergence in $J_T(\hat{\beta})$'s small sample distribution from a χ^2_8. In order to extend the analysis to the stock returns' sample distributions, we calculate monte carlo p-values for each of the 29 portfolios from its own empirical distribution of 5000 repetitions.

These results are given in the second column of Table 3. Only one portfolio's serial correlation pattern is signficant at the 10% empirical p-value — specifically, utilities has a $J_T(\hat{\beta})$ statistic of 26.98 which represents the 3.44% empirical level. It is interesting to note that utilities is one of the least significant portfolios in terms of t statistics. Utilities' serial correlation pattern over the 1-6, 8 and 10 year horizons is -5%,-16%,-27%,-22%,-2%,24%,14% and 10%, respectively. Consider the asymptotic correlation between the 5,6 and 8-year serial correlation estimators:

$$corr\begin{pmatrix}\hat{\beta}_{60}\\ \hat{\beta}_{72}\\ \hat{\beta}_{96}\end{pmatrix} = \begin{pmatrix}1.00 & .95 & .73\\ .95 & 1.00 & .88\\ .73 & .88 & 1.00\end{pmatrix}.$$

Conditional on $\hat{\beta}_{60} = -.02$, $\hat{\beta}_{96} = .14$, and the correlation matrix above, we would expect $\hat{\beta}_{72}$ to lie between -2% and 14% under the random walk null. Therefore, even though these estimates are small in magnitude, $\hat{\beta}_{72} = .24$ in the joint setting imposes sharp evidence against the null. (Note that utilities' significant serial correlation pattern may be due to sampling error, i.e. we have reported individual results for 29 portfolios and found only one deviation from the random walk model. This issue is addressed in Section 3.2.)

3.1.2 Additional Holding Periods

To coincide with an earlier version of Fama and French (1987), we report autocorrelation patterns for additional holding periods (including the 7- and 9-year horizons). The results are provided in Table 4 and now, somewhat surprisingly, reject the random walk model. For example, as a representative portfolio, consider the sixth size decile portfolio. Its serial correlation pattern over the 1-10 year horizons is -5%,-21%,-30%,-30%,-28%,-10%,7%,3%, 11% and 12%. Note that there is a spike in the autocorrelation estimate at the 7-year horizon (i.e. 7%) which is not consistent with the correlation matrix between the 7-year autocorrelation estimator and its surrounding estimators. Of particular interest, column 5 of Table 4 reports the 7-year autocorrelation estimates across the portfolios, and it is evident that the 7-year spike is present in all of the portfolios. However, the estimates tend to be positive and small in magnitude; for example, the average across the portfolios is approximately 8%.

In terms of temporary components of stock prices, most of the discussion concerning mean reversion has focused on the "apparent" large magnitude of the serial correlation estimates of the 3-5 year returns. Heuristically, if the 3-5 year holding period returns are an important part of this 7-year relation, then one should expect that upon removal of these returns the $J_T(\hat{\beta})$ statistic would significantly decrease in value. Of course, $J_T(\hat{\beta})$ no longer has an asymptotic χ^2 distribution since we have removed the maximal autocorrelations. Nevertheless, if anything, we would expect removing the maximal autocorrelations to sharply reduce the tails of $J_T(\hat{\beta})$'s distribution. In addition, some decrease is expected because three restrictions from the $J_T(\hat{\beta})$ statistic have been removed. The results for the $J_T(\hat{\beta})$ statistic for the size and industry portfolios over years 1-2 and 6-10 are given in column 6 of Table 4. In almost all the cases, the statistic barely drops in value. The 3-5 year return horizon contributes little to the statistic's value and, therefore, does not seem to play an important role in the resulting rejection of the random walk.

3.1.3 Heteroskedasticity in Stock Returns

There is growing evidence that stock returns are heteroskedastic. For example, Bollerslev, Engle and Wooldridge (1988), French, Schwert and Stambaugh (1987), Schwert (1989) and others find that that stock return variances tend to be positively autocorrelated. It is, therefore, of some interest to study heteroskedasticity's impact on the empirical results in Sections 3.2.1 and 3.2.2. In particular, under mild assumptions, it is possible to show that the typical elements of the asymptotic heteroskedasticity consistent variance-covariance matrix of the $\hat{\beta}$'s are

$$var\begin{pmatrix}\hat{\beta}_j\\ \hat{\beta}_k\end{pmatrix} + \begin{pmatrix} \sum_{i=1}^{2j-1}\left(\frac{min(i,2j-i)}{j}\right)^2 \frac{cov(R_t^2,R_{t-i}^2)}{\sigma_R^4} & \sum_{i=1}^{2k-1}\left(\frac{m_i(j,k)}{jk}\right)\frac{cov(R_t^2,R_{t-i}^2)}{\sigma_R^4} \\ \sum_{i=1}^{2k-1}\left(\frac{m_i(j,k)}{jk}\right)\frac{cov(R_t^2,R_{t-i}^2)}{\sigma_R^4} & \sum_{i=1}^{2k-1}\left(\frac{min(i,2k-i)}{k}\right)^2 \frac{cov(R_t^2,R_{t-i}^2)}{\sigma_R^4}\end{pmatrix},$$

where $m_i(j,k) = min[i, max(2j-i,0)]min(i,2k-i)$.

For each portfolio, we recalculate the $J_T(\hat{\beta})$ statistic using its heteroskedasticity consistent variance. The results are given in columns 4 and 5 of Table 3 and columns 7 and 8 of Table 4. The statistic's value barely changes for both [1-6,8,10] and [1-10] year returns. Note that the driving force behind the evidence in Table 4 is that the 7-year spike in the autocorrelation estimates is inconsistent with the correlation matrix between $\hat{\beta}_{84}$ and surrounding $\hat{\beta}$'s. Since heteroskedasticity impacts both the covariance and variance of these long-horizon $\hat{\beta}$'s, it washes out — leaving the correlation matrix intact. Hence, heteroskedasticity does not explain this long-horizon evidence.

3.2 Multivariate Test

One of the striking features of the multiperiod autocorrelation evidence is that it is pervasive across the different portfolios. While intuition might suggest that these portfolios, which exhibit similar serial correlation behavior, provide strong evidence against the random walk, we must be careful to interpret the estimates in the proper context. Under the random walk model, we should expect to find that highly correlated portfolios have similar multiperiod autocorrelation patterns.

In Section 3.1, we reported $J_T(\hat{\beta})$ statistics for each of the 29 different portfolios. In general, the returns on these portfolios will be correlated; therefore, for testing the hypothesis that all the portfolio's stock prices follow a random walk, the test statistic should incorporate the correlation across portfolios. Under analogous assumptions to Section 3.1, it is possible to show that the corresponding Wald statistic in this multivariate setting is given by

$$J_T^{mv}(\hat{\beta}) \equiv T\hat{\beta}^N[(\hat{\Sigma}^N)^{-1} \otimes V(\hat{\beta})^{-1}](\hat{\beta}^N)' \sim \chi^2_{N\times S}.$$

where $\hat{\beta}^N$ is a $1 \times (S \times N)$ vector of S multiperiod autocorrelations across the N assets, $\hat{\Sigma}^N$ is the $N \times N$ matrix of squared sample correlation coefficients between the N assets, and and $V(\hat{\beta})$ is the $S \times S$ variance-covariance matrix of the autocorrelation estimators. The test results for this statistic are given in Table 5.

The value of $J_T^{mv}(\hat{\beta})$ is 115 and 269 respectively for the 10 size and 17 industry portfolios over the 1-6,8 and 10-year horizons. The corresponding monte carlo empirical p-values are only 40.7% and 20.5%, suggesting little evidence against the random walk model. For example, consider the 10 size portfolios. The results should not be particularly surprising given that the correlation across the size portfolios ranges from .74 to .98. It is evident from Table 1 that the size portfolios which are most (least) correlated also have the most (least) similar correlation patterns. For example, consider the least correlated portfolios; that is, deciles 1 and 10 have a .74 correlation. Their serial correlation patterns are [.01,-.13,-.23,-.36,-.32,-.32,-.05,.35,.56] and [-.06,-.23,-.27,-.10,.05,.25,.34,.25], respectively. In contrast, the more correlated portfolios (i.e. deciles 4–6) have almost identical magnitudes and patterns of serial correlation in common. This is what we would expect under the random walk null.

When we extend the multivariate results to include the additional time horizons, the cross-correlation pattern across the assets cannot completely explain the intertemporal behavior of stock returns in terms of a random walk. In particular, the value of $J_T^{mv}(\hat{\beta})$ for the 10 size and 17 industry portfolios is now 421 and 623 which represents the 8.8% and 9.5% monte carlo empirical p-values. Hence, even though the 7-year autocorrelation spike is present in all the portfolios' serial correlation patterns, it evidently is not consistent with the correlation matrix across assets.

3.3 Power Discussion

One possible explanation of the results in Sections 2 and 3 is that the maximum statistics and the wald statistics have low power against mean-reversion alternatives relative to the power of individual autocorrelation statistics. It seems appropriate. therefore, to compare the power of the joint test statistic $J_T(\hat{\beta})$ to t-statistics for the individual multiperiod autocorrelation estimator $\hat{\beta}_j$. For example, consider the Fama-French/Poterba-Summers temporary component model in which stock prices have a random walk and a first-order autoregressive component. To coincide with Poterba-Summers (1988), assume that the

$AR(1)$ parameter equals .975 and that the stationary component captures $\frac{3}{4}$th of the variance in returns. Using the simulation method of Section 2, we calculate the power of the $J_T(\hat{\beta})$ statistic and (for purposes of comparison) the 5-year autocorrelation estimator. For 5% and 10% size tests, the $J_T(\hat{\beta})$ statistic has 9.58% and 19.2% power, respectively. In contrast, using a two-sided test at these levels, the individual 5-year serial correlation estimator, $\hat{\beta}_{60}$, has only 3.9% and 9.9% power. Given these calculations, there is little to suggest that differences between the individual and joint tests are due to power.

On the other hand, a number of recent papers (e.g. Jegadeesh (1991) and Jacquier and Nanda (1988)) use alternative individual test statistics and report somewhat stronger evidence in favor of a temporary component of stock prices. These results, however, need to be interpreted in context with the multiperiod autocorrelation estimates. Note that searching for more powerful statistics against mean-reversion can lead to mistaken conclusions because the alternative theory came from observing the data. This impacts the size of the "more powerful" statistics as they are estimated sequentially. Conditional upon observing the U-shaped pattern in the serial correlation estimates, we would expect to find that these alternative statistics pick-up mean reversion. Since in this sequential setting only random walk data producing U-shaped patterns are relevant, the size of these alternative statistics will dramatically increase.

4 Conclusion

There are several conclusions to be reached from this paper. First, we provide an alternative interpretation of recent evidence regarding serial dependency in stock returns. Note that prior to the evidence of large negative autocorrelations, there had been little discussion in the finance literature concerning models of stock price behavior which could exhibit the types of patterns observed in the data. In fact, the long-horizon evidence has received much attention precisely because they have changed the finance profession's view that long-term stock returns are for the most part unpredictable. This paper shows that the estimates and corresponding serial dependence patterns should be **expected** from random walk data.

Second, we document evidence for joint tests across different return horizons. A number of the tests cannot reject the null hypothesis that stock returns follow a random walk. Of particular interest:

- This conclusion appears valid even when we take account of heteroskedasticity in the data.

- The results do not seem due to differences in power between the joint and individual test statistics.
- Perhaps most surprising, these results hold across assets. That is, the serial correlation patterns are those we might expect from random walk data given the particular degree of correlation across assets.

On a different note, however, we did document some evidence that stock returns are serially correlated over the various horizons. This predictability, however, was positive and small in magnitude. Although this evidence may also be spurious in small samples, we found that it is pervasive across different assets and cannot be explained by the cross-correlation pattern of asset returns.

TABLE 1

Summary of Multiperiod Autocorrelations (1926-85)

Return Horizon (years 1-6,8,10)

Table 1 reports multiperiod autocorrelation estimates over (1-6,8 and 10)-year horizons. Denote these estimates $\hat{\beta}_j$, where j equals the length of the horizon in months. These estimates are taken from Fama and French (1988), Tables 1 and 2. In particular, the estimates involve the regression of j-period returns on past j-period returns using overlapping data. The estimates are adjusted to reflect bias in small samples.

Portfolio	$\hat{\beta}_{12}$	$\hat{\beta}_{24}$	$\hat{\beta}_{36}$	$\hat{\beta}_{48}$	$\hat{\beta}_{60}$	$\hat{\beta}_{72}$	$\hat{\beta}_{96}$	$\hat{\beta}_{120}$
Food	-.01	-.24	-.34	-.36	-.34	-.15	.01	.08
Apparel	-.08	-.18	-.20	-.27	-.30	-.21	-.21	-.27
Drugs	-.02	-.14	-.18	-.12	-.13	-.06	-.09	-.22
Retail	-.01	-.17	-.30	-.32	-.33	-.18	-.10	-.02
Durables	.02	-.14	-.26	-.33	-.30	-.09	.02	.13
Autos	-.05	-.22	-.36	-.42	-.35	-.13	-.04	-.02
Construction	-.01	-.13	-.27	-.41	-.42	-.21	.16	.24
Finance	-.01	-.17	-.26	-.25	-.15	.07	.22	.35
Miscellaneous	-.02	-.13	-.25	-.35	-.37	-.18	.00	.12
Utilities	-.05	-.16	-.27	-.22	-.02	.24	.14	.10
Transportation	-.10	-.20	-.26	-.33	-.32	-.18	-.09	.02
Bus. Equipment	.01	-.22	-.39	-.41	-.36	-.19	.05	.13
Chemicals	-.04	-.33	-.43	-.38	-.37	-.19	.01	.12
Metal Prod.	.01	-.20	-.38	-.49	-.52	-.37	-.16	-.05
Metal Ind.	-.08	-.27	-.36	-.36	-.35	-.17	.18	.28
Mining	-.09	-.29	-.37	-.44	-.48	-.28	.02	.08
Oil	-.02	-.23	-.29	-.42	-.40	-.20	.17	.27
Size Decile 1	.01	-.13	-.23	-.36	-.32	-.05	.35	.56
Size Decile 2	.01	-.12	-.25	-.41	-.45	-.26	-.02	.09
Size Decile 3	-.04	-.16	-.27	-.35	-.35	-.19	-.08	-.04
Size Decile 4	-.02	-.19	-.29	-.38	-.39	-.23	-.08	.05
Size Decile 5	-.06	-.23	-.29	-.32	-.33	-.16	-.01	.13
Size Decile 6	-.05	-.20	-.31	-.31	-.28	-.10	.04	.13
Size Decile 7	-.07	-.27	-.35	-.28	-.22	-.02	.12	.16
Size Decile 8	-0.05	-.23	-.30	-.20	-.13	.06	.15	.15
Size Decile 9	-.04	-.21	-.27	-.13	-.01	.21	.30	.25
Size Decile 10	-.06	-.23	-.27	-.10	.05	.25	.34	.25
Equal Wt.	-.05	-.22	-.32	-.36	-.34	-.13	.08	.22
Value Wt.	-.03	-.20	-.25	-.09	.06	.25	.31	.21

TABLE 2

Empirical Distribution of Maximum Multiperiod Autocorrelations Across Return Horizons: [1-6,8,10] years (720 obs.)

Table 2 reports the empirical distribution of the j-period serial correlation estimators' largest absolute deviation from zero across horizons $j \in \{12, 24, \ldots, 72, 96, 120\}$. Denote this statistic $\hat{\beta}_{j^*}$, where j^* is the period in which the largest deviation occurs. The distribution is computed using 5000 replications of data generated from an i.i.d. normally distributed random variable (in which the mean and variance are chosen to match the equal-weighted stock return index). Also provided are the empirical distributions of $|\hat{\beta}_{j^*}|$ and $\hat{\beta}_{j^*}$ (when $j^* \in \{36, 48, 60\}$).

A.
Frequency Distribution for j^*

	yr. 1	yr. 2	yr. 3	yr. 4	yr. 5	yr. 6	yr. 8	yr. 10
Percentage	3%	7.12%	8.86%	8.42%	8.76%	13.46%	17.32%	33.06%

B.
Empirical Distribution of $\hat{\beta}_{j^*}$

		Empirical CDF Values						
Statistic	Mean	.05	.25	.415	.50	.585	.75	.95
$\hat{\beta}_{j^*}$	-.022	-.531	-.340	-.234	-.171	.170	.305	.572
$\lvert\hat{\beta}_{j^*}\rvert$	.353	.147	.238	.244	.323	.355	.432	.636
$\hat{\beta}_{j^*}(j^* \in \{3, 4, 5\})$	.301	-.4703	-.2985	-.1983	.0858	.1846	.2747	.4396

TABLE 3

Joint Test Statistics for Portfolio Returns (1926-1985)

Return Horizon (years 1-6,8,10)

Table 3 reports F tests (denote $J_T(\hat{\beta})$) for whether the serial correlation estimates of 1-6, 8 and 10 year returns on 29 different portfolios (i.e. 2 index, 10 size and 17 industry) are each jointly significantly different from zero. Columns 5 and 6 report heteroskedasticity consistent $J_T(\hat{\beta})$ statistics. Columns 7 and 8 provide the $\max_j |\hat{\beta}_j|$ statistic taken from the actual data across the 1-6,8 and 10 year horizons for each portfolio. The tests are performed on overlapping monthly returns for the period 1926 - 1985. The empirical p-value is the p-value for the statistic generated from each portfolio's empirical distribution under the null hypothesis. This distribution was computed from 5000 replications using data independently drawn with replacement from the sample distribution of each portfolio's returns.

Portfolio	$J_T(\hat{\beta})$	χ^2_8 p-value	Empirical p-value	Heterosked. $J_T(\hat{\beta})$	χ^2_8 p-value	$\max_j \lvert\hat{\beta}_j\rvert$	Empirical p-value
Food	12.03	.1500	.2664	12.96	.1133	.36	.41
Apparel	7.35	.4996	.5764	7.47	.4872	.30	.60
Drugs	7.26	.5099	.6008	9.10	.3338	.22	.84
Retail	10.76	.2155	.3420	11.85	.1582	.33	.50
Durables	15.41	.0517	.2664	19.09	.0144	.33	.50
Autos	14.72	.0647	.1618	13.81	.0868	.42	.25
Construction	12.76	.1204	.1804	13.22	.1045	.42	.26
Finance	11.03	.2002	.2522	13.47	.0966	.35	.44
Miscellaneous	12.30	.1383	.2580	11.76	.1624	.37	.38
Utilities	26.98	.0007	.0344	28.52	.0004	.27	.69
Transportation	9.27	.3203	.4092	10.74	.2170	.33	.50
Bus. Equipment	8.29	.4061	.4958	8.34	.4005	.41	.28
Chemicals	15.54	.0494	.1590	15.54	.0494	.43	.23
Metal Prod.	10.28	.2461	.3516	8.47	.3890	.52	.12
Metal Ind.	13.48	.0964	.2132	13.52	.0951	.36	.41
Mining	17.79	.0228	.1104	19.31	.0133	.48	.16
Oil	12.51	.1295	.2482	13.29	.1022	.42	.26
Size Decile 1	15.48	.0504	.1652	11.93	.1543	.56	.09
Size Decile 2	13.06	.1097	.2200	10.84	.2108	.45	.20
Size Decile 3	9.15	.3295	.4282	9.55	.2980	.35	.44
Size Decile 4	10.47	.2336	.3364	10.74	.2166	.39	.33
Size Decile 5	11.85	.1581	.2770	11.68	.1663	.33	.50
Size Decile 6	9.78	.2809	.3968	9.93	.2700	.31	.56
Size Decile 7	12.35	.1363	.2624	12.14	.1452	.35	.45
Size Decile 8	11.79	.1609	.2878	14.39	.0722	.30	.60
Size Decile 9	12.56	.1280	.2562	11.87	.1571	.30	.60
Size Decile 10	10.14	.2551	.3716	10.93	.2059	.34	.47
Eq. Wt.	12.52	.1295	.2578	NA	NA	.36	.41
Val Wt.	8.96	.3454	.4604	NA	NA	.36	.41
Average	12.27	.1910	.3045	12.76	.1748	.31	.42

TABLE 4

Joint Test Statistics for Portfolio Returns (1926-1985)

Return Horizon (years 1-10)

Table 4 reports F tests (denote $J_T(\hat{\beta})$) for whether the serial correlation estimates of 1-10 year returns on 27 different portfolios (i.e. 10 size and 17 industry) are jointly significantly different from zero. The test is performed on overlapping monthly returns for the period 1926 – 1985. In addition, Column 5 reports the 7-year multiperiod autocorrelation estimate, $\hat{\beta}_{84}$. Column 6 calculates $J_T(\hat{\beta})$ for 1-2 and 6-10 year horizons. Columns 7 and 8 report heteroskedasticity consistent $J_T(\hat{\beta})$ statistics for 1-10 year horizons.

Portfolio	$J_T(\hat{\beta})$	χ^2_{10} p-value	Empirical p-value	$\hat{\beta}_{84}$	Yrs. 1-2,6-10 $J_T(\hat{\beta})$		Heterosked. $J_T(\hat{\beta})$	χ^2_{10} p-value
Food	41.58	.0000	.0540	.07	38.70		41.84	.0000
Apparel	16.94	.0757	.3150	-.13	13.86		18.15	.0525
Drugs	16.63	.0829	.3220	-.01	13.20		20.11	.0282
Retail	38.34	.0000	.0640	-.01	36.01		46.53	.0000
Durables	56.66	.0000	.0236	.11	53.91		71.08	.0000
Autos	47.74	.0000	.0378	.05	45.59		50.10	.0000
Construction	36.70	.0001	.0702	.09	34.98		43.25	.0000
Finance	34.58	.0001	.0800	.23	32.95		45.71	.0000
Miscellaneous	29.42	.0011	.1144	.02	26.04		32.87	.0003
Utilities	46.70	.0000	.0404	.30	36.62		51.47	.0000
Transportation	32.71	.0003	.0908	-.04	30.63		37.18	.0001
Bus. Equipment	47.26	.0000	.0390	.03	46.32		64.76	.0000
Chemicals	55.61	.0000	.0250	.04	51.64		62.03	.0000
Metal Prod.	49.43	.0000	.0350	-.17	48.83		60.63	.0000
Metal Ind.	33.73	.0002	.0854	.11	29.47		37.45	.0000
Mining	44.63	.0000	.0448	.01	37.78		47.12	.0000
Oil	26.83	.0028	.1356	.08	21.09		28.98	.0018
Size Decile 1	30.14	.0009	.1098	.21	26.20		33.40	.0002
Size Decile 2	32.51	.0005	.0910	-.03	28.77		32.42	.0003
Size Decile 3	33.59	.0003	.0872	-.01	31.37		38.15	.0000
Size Decile 4	33.68	.0003	.0860	-.04	31.32		37.33	.0000
Size Decile 5	43.92	.0000	.0472	.04	41.72		48.80	.0000
Size Decile 6	33.55	.0004	.0862	.07	32.72		38.57	.0000
Size Decile 7	54.52	.0000	.0260	.19	52.52		60.83	.0000
Size Decile 8	47.00	.0000	.0400	.24	44.30		52.09	.0000
Size Decile 9	41.32	.0000	.0544	.37	40.22		48.93	.0000
Size Decile 10	46.32	.0000	.0414	.42	43.97		57.89	.0000
Average	38.96	.0061	.0832	.08	35.95		44.73	.0031

TABLE 5

Multivariate Joint Test Statistics

Table 5 reports F tests (denote $J_T^{mv}(\hat{\beta})$) for whether the multiyear serial correlation estimates across the size and industry portfolio returns (1926-85) are jointly significantly different from zero. Specifically, we report F tests across [1-6,8,10] and [1-10] year horizons for the 10 size and 17 industry portfolios. Panel A provides the small sample empirical distribution of $J_T^{mv}(\hat{\beta})$, generated from 5000 replications of data independently drawn from the joint sample distribution of returns. Panel B provides the F test results with corresponding empirical p-value.

A.

Empirical Distribution of $J_T^{mv}(\hat{\beta})$

$J_T^{mv}(\hat{\beta})$ Assets [yrs]	Mean	Empirical CDF Values .05	.10	.30	.50	.70	.90	.95
Size [1-6,8,10]	123.5	52.5	60.1	81.0	103.3	134.9	207.7	263.2
Size [1-10]	217.3	67.1	79.7	119.5	164.8	232.6	401.4	537.6
Industry [1-6,8,10]	209.2	96.5	109.3	147.4	184.7	232.2	336.5	406.9
Industry [1-10]	352.9	126.5	146.2	214.5	288.2	390.4	610.6	761.4

B.

$J_T^{mv}(\hat{\beta})$ (1926-1985)

	10 size [1-6,8,10] yrs	10 size [1-10] yrs	17 industry [1-6,8,10] yrs	17 industry [1-10] yrs
$J_T^{mv}(\hat{\beta})$	116.2	421.8	269.5	623.3
Empirical p-value	.4070	.0880	.2050	.0950

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