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Author(s): Eugene F. Fama and Kenneth R. French
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Permanent and Temporary Components of Stock Prices

Eugene F. Fama and Kenneth R. French

University of Chicago

A slowly mean-reverting component of stock prices tends to induce negative autocorrelation in returns. The autocorrelation is weak for the daily and weekly holding periods common in market efficiency tests but stronger for long-horizon returns. In tests for the 1926–85 period, large negative autocorrelations for return horizons beyond a year suggest that predictable price variation due to mean reversion accounts for large fractions of 3–5-year return variances. Predictable variation is estimated to be about 40 percent of 3–5-year return variances for portfolios of small firms. The percentage falls to around 25 percent for portfolios of large firms.

I. Introduction

Early tests of market efficiency examined autocorrelations of daily and weekly stock returns. Sample sizes for such short return horizons are typically large, and reliable evidence of nonzero autocorrelation is common. Since the estimated autocorrelations are usually close to 0.0, however, most studies conclude that the implied predictability of returns is not economically significant. Fama (1970) summarizes this early work, which largely concludes that the stock market is efficient.

Summers (1986) challenges this interpretation of the autocorrelation of short-horizon returns. He argues that the claim in common

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models of an inefficient market is that prices take long temporary swings away from fundamental values, which he translates into the statistical hypothesis that prices have slowly decaying stationary components. He shows that autocorrelations of short-horizon returns can give the impression that such mean-reverting components of prices are of no consequence when in fact they account for a substantial fraction of the variation of returns.

Our tests are based on the converse proposition that the behavior of long-horizon returns can give a clearer impression of the importance of mean-reverting price components. Specifically, a slowly decaying component of prices induces negative autocorrelation in returns that is weak for the daily and weekly holding periods common in market efficiency tests. But such a temporary component of prices can induce strong negative autocorrelation in long-horizon returns.

We examine autocorrelations of stock returns for increasing holding periods. In the results for the 1926–85 sample period, large negative autocorrelations for return horizons beyond a year are consistent with the hypothesis that mean-reverting price components are important in the variation of returns. The estimates for industry portfolios suggest that predictable variation due to mean reversion is about 35 percent of 3–5-year return variances. Returns are more predictable for portfolios of small firms. Predictable variation is estimated to be about 40 percent of 3–5-year return variances for small-firm portfolios. The percentage falls to around 25 percent for portfolios of large firms.

Our results add to mounting evidence that stock returns are predictable (see, e.g., Bodie 1976; Jaffe and Mandelker 1976; Nelson 1976; Fama and Schwert 1977; Fama 1981; Campbell 1987; French, Schwert, and Stambaugh 1987). Again, this work focuses on short return horizons (De Bondt and Thaler [1985] are an exception), and the common conclusion is that predictable variation is a small part (usually less than 3 percent) of the variation of returns. There is little in the literature that foreshadows our estimates that 25–45 percent of the variation of 3–5-year stock returns is predictable from past returns.

There are two competing economic stories for strong predictability of long-horizon returns due to slowly decaying price components. Such price behavior is consistent with common models of an irrational market in which stock prices take long temporary swings away from fundamental values. But the predictability of long-horizon returns can also result from time-varying equilibrium expected returns generated by rational pricing in an efficient market. Poterba and Summers (1987) show formally how these opposite views can imply the same price behavior. The intuition is straightforward.

Expected returns correspond roughly to the discount rates that relate a current stock price to expected future dividends. Suppose that investor tastes for current versus risky future consumption and the stochastic evolution of the investment opportunities of firms result in time-varying equilibrium expected returns that are highly autocorrelated but mean-reverting. Suppose that shocks to expected returns are uncorrelated with shocks to rational forecasts of dividends. Then a shock to expected returns has no effect on expected dividends or expected returns in the distant future. Thus the shock has no long-term effect on expected prices. The cumulative effect of a shock on expected returns must be exactly offset by an opposite adjustment in the current price.

In this scenario, autocorrelated equilibrium expected returns lead to slowly decaying components of prices that are indistinguishable from the temporary price components of an inefficient market, at least with univariate tests like those considered here. More informed choices between the competing explanations of return predictability will require models that restrict the variation of expected returns in plausible ways, for example, models that restrict the relations between the behavior of macroeconomic driving variables and equilibrium expected returns.

Finally, tests on long-horizon returns can provide a better impression of the importance of slowly decaying stationary price components, but the cost is statistical imprecision. The temporary component of prices must account for a large fraction of return variation to be identified in the univariate properties of long-horizon returns. We find "reliable" evidence of negative autocorrelation only in tests on the entire 1926–85 sample period, and the evidence is clouded by the statistical issues (changing parameters, heteroscedasticity, etc.) that such a long time period raises.

II. A Simple Model for Stock Prices

Let $p(t)$ be the natural log of a stock price at time t. We model $p(t)$ as the sum of a random walk, $q(t)$, and a stationary component, $z(t)$,

$$p(t) = q(t) + z(t), \tag{1}$$

$$q(t) = q(t - 1) + \mu + \eta(t), \tag{2}$$

where μ is expected drift and $\eta(t)$ is white noise. Summers (1986) argues that the long temporary price swings assumed in models of an inefficient market imply a slowly decaying stationary price component. As an example, he suggests a first-order autoregression (AR1),

$$z(t) = \phi z(t - 1) + \epsilon(t), \tag{3}$$

where $\epsilon(t)$ is white noise and ϕ is close to but less than 1.0.

The model (1)–(3) is just one way to represent a mix of random-walk and stationary price components. The general hypothesis is that stock prices are nonstationary processes in which the permanent gain from each month's price shock is less than 1.0. Our tests are relevant for the general class of models in which part of each month's shock is permanent and the rest is gradually eliminated. The tests center on the fact that the temporary part of the shock implies predictability (negative autocorrelation) of returns.

A. *The Implications of a Stationary Price Component*

Since $p(t)$ is the natural log of the stock price, the continuously compounded return from t to $t + T$ is

$$\begin{aligned} r(t, t + T) &= p(t + T) - p(t) \\ &= [q(t + T) - q(t)] + [z(t + T) - z(t)]. \end{aligned} \tag{4}$$

The random-walk price component produces white noise in returns. We show next that the mean reversion of the stationary price component $z(t)$ causes negative autocorrelation in returns.

The slope in the regression of $z(t + T) - z(t)$ on $z(t) - z(t - T)$, the first-order autocorrelation of T-period changes in $z(t)$, is

$$\rho(T) = \frac{\text{cov}[z(t + T) - z(t), z(t) - z(t - T)]}{\sigma^2[z(t + T) - z(t)]}. \tag{5}$$

The numerator covariance is

$$\begin{aligned} \text{cov}[z(t + T) - z(t), z(t) - z(t - T)] = &-\sigma^2(z) + 2\,\text{cov}[z(t), z(t + T)] \\ &- \text{cov}[z(t), z(t + 2T)]. \end{aligned} \tag{6}$$

The stationarity of $z(t)$ implies that the covariances on the right of (6) approach 0.0 as T increases, so the covariance on the left approaches $-\sigma^2(z)$. The variance in the denominator of the slope,

$$\sigma^2[z(t + T) - z(t)] = 2\sigma^2(z) - 2\,\text{cov}[z(t + T), z(t)], \tag{7}$$

approaches $2\sigma^2(z)$. We can infer from (6) and (7) that the slope in the regression of $z(t + T) - z(t)$ on $z(t) - z(t - T)$ approaches -0.5 for large T.

The slope $\rho(T)$ has an interesting interpretation used often in the empirical work of later sections. If $z(t)$ is an AR1, the expected change from t to T is

$$E_t[z(t + T) - z(t)] = (\phi^T - 1)z(t), \tag{8}$$

and the covariance in the numerator of $\rho(T)$ is

$$\begin{aligned} \operatorname{cov}[z(t + T) - z(t), z(t) - z(t - T)] &= (-1 + 2\phi^T - \phi^{2T})\sigma^2(z) \\ &= -(1 - \phi^T)^2\sigma^2(z). \end{aligned} \tag{9}$$

With (8) and (9) we can infer that the covariance is minus the variance of the T-period expected change, $-\sigma^2[E_t z(t + T) - z(t)]$. Thus, when $z(t)$ is an AR1, the slope in the regression of $z(t + T) - z(t)$ on $z(t) - z(t - T)$ is (minus) the ratio of the variance of the expected change in $z(t)$ to the variance of the actual change. This interpretation of the slope is a valid approximation for any slowly decaying stationary process.[1]

Equation (8) shows that when ϕ is close to 1.0, the expected change in an AR1 slowly approaches $-z(t)$ as T increases. Likewise, the slope $\rho(T)$ is close to 0.0 for short return horizons and slowly approaches -0.5. This illustrates Summers's (1986) point that slow mean reversion can be missed with the short return horizons common in market efficiency tests. Our tests are based on the converse insight that slow mean reversion can be more evident in long-horizon returns.

B. The Properties of Returns

Since we do not observe $z(t)$, we infer its existence and properties from the behavior of returns. Let $\beta(T)$ be the slope in the regression of the return $r(t, t + T)$ on $r(t - T, t)$. If changes in the random-walk and stationary components of stock prices are uncorrelated,

$$\beta(T) = \frac{\operatorname{cov}[r(t, t + T), r(t - T, t)]}{\sigma^2[r(t - T, t)]} \tag{10}$$

$$= \frac{\rho(T)\sigma^2[z(t + T) - z(t)]}{\sigma^2[z(t + T) - z(t)] + \sigma^2[q(t + T) - q(t)]} \tag{10a}$$

[1] For long return horizons, the interpretation of the slope as the proportion of the variance of the change in $z(t)$ due to the expected change is valid for any stationary process. If $z(t)$ is a stationary process with a zero mean, the expected change from t to T approaches $-z(t)$ as T increases, and the variance of the expected change approaches $\sigma^2(z)$. The ratio of the long-horizon variance of the expected change in $z(t)$, $\sigma^2(z)$, to the long-horizon variance of the actual change, $2\sigma^2(z)$, is thus 0.5, the negative of the long-horizon value of $\rho(T)$.

$$\approx \frac{-\sigma^2[E_t z(t + T) - z(t)]}{\sigma^2[r(t - T, t)]}. \tag{10b}$$

Expression (10b) highlights the result that $\beta(T)$ measures the proportion of the variance of T-period returns explained by (or predictable from) the mean reversion of a slowly decaying price component $z(t)$. Expression (10a) helps predict the behavior of the slopes for increasing values of T. If the price does not have a stationary component, the slopes are 0.0 for all T. If the price does not have a random-walk component, $\beta(T) = \rho(T)$ and the slopes approach -0.5 for large values of T.

Predictions about the slope $\beta(T)$ are more complicated if the stock price has both random-walk and stationary components. The mean reversion of the stationary component tends to push the slopes toward -0.5 for long return horizons, while the variance of the white-noise component, $q(t + T) - q(t)$, pushes the slopes toward 0.0. Since the variance of $z(t + T) - z(t)$ approaches $2\sigma^2(z)$ as the return horizon increases and the white-noise variance grows like T, the white-noise component eventually dominates. Thus, if stock prices have both random-walk and slowly decaying stationary components, the slopes in regressions of $r(t, t + T)$ on $r(T - t, t)$ might form a U-shaped pattern, starting around 0.0 for short horizons, becoming more negative as T increases, and then moving back toward 0.0 as the white-noise variance begins to dominate at long horizons.

Finally, existing evidence (e.g., Fama and Schwert 1977; Keim and Stambaugh 1986; Fama and French 1987; French et al. 1987) suggests that expected returns are positively autocorrelated. The negative autocorrelation of long-horizon returns due to a stationary component of prices is consistent with positively autocorrelated expected returns. For example, the model (1)–(3) implies negatively autocorrelated returns. Poterba and Summers (1987) show, however, that if the stationary price component $z(t)$ in (3) is an AR1 with parameter $\phi > 0.0$, the expected return is an AR1 with parameter ϕ and so is positively autocorrelated. The economic intuition is that shocks to expected returns (discount rates) can generate opposite shocks to current prices, and returns can be negatively autocorrelated when expected returns are positively autocorrelated.

III. The Autocorrelation of Industry and Decile Portfolio Returns

A. *The Data*

The mix of random-walk and stationary components in stock prices can differ across stocks. Firm size and industry are dimensions known to capture differences in return behavior (see King 1966; Banz 1981; Huberman and Kandel 1985). We examine results for industry portfolios and for portfolios formed on the basis of size.

The basic data are 1-month returns for all New York Stock Exchange (NYSE) stocks for the 1926–85 period from the Center for Research in Security Prices. At the end of each year, stocks are ranked on the basis of size (shares outstanding times price per share) and grouped into ten (decile) portfolios. One-month portfolio returns, with equal weighting of securities, are calculated and transformed into continuously compounded returns. These nominal returns are adjusted for the inflation rate of the U.S. Consumer Price Index (CPI) and then summed to get overlapping monthly observations on longer-horizon returns. Unless otherwise noted, return henceforth implies a continuously compounded real return.

There is a problem with the decile portfolios. Stocks with unusually high or low returns tend to move across deciles from one year to the next. If unusual returns are caused by temporary price swings, subsequent reversals may be missed—the tests may understate the importance of stationary price components—because of the movement of stocks across deciles. Since the problem is less severe for portfolios that include all stocks, we also show results for the equal- and value-weighted portfolios of all NYSE stocks. The value-weighted market portfolio summarizes the return behavior of large stocks, while the equal-weighted portfolio is tilted more toward small stocks.

Using Standard Industrial Classification codes, we also form 17 industry portfolios, with equal weighting of the stocks in a portfolio. One criterion in defining an industry is that it contains firms in similar activities. The other criterion is that the industry produces diversified portfolios during the 1926–85 period. Each of the 17 industries always has at least seven firms (15 after 1929), and the number of firms per industry is usually greater than 30. Within industries, there is little concentration of firms by size. For example, the average of the decile ranks of the firms in an industry is typically between 4.0 and 7.0. Thus size and industry are not proxies, and size and industry portfolios can provide independent evidence on the behavior of long-horizon returns. (Details on the industry portfolios are available from the authors.)

The tests center on slopes in regressions of $r(t, t + T)$ on $r(t - T, t)$. The slopes are first-order autocorrelations of T-year returns. Ordinary least squares (OLS) estimates have a bias that depends on the true slopes, sample sizes, and the overlap of monthly data on long-horizon returns (see Kendall 1954; Marriot and Pope 1954; Huizinga 1984). Proper bias adjustments when the true slopes are 0.0 (prices do not have stationary components) are difficult to determine analytically. We use simulations, constructed to mimic properties of stock returns, to estimate the bias adjustments (see the Appendix). The simulations also show that when prices have stationary components that generate negative autocorrelations on the order of those observed here, simple OLS slopes have little bias. We examine both OLS and bias-adjusted slopes.

B. Regression Slopes for the 1926–85 Sample Period

Industries

Table 1 shows slopes in regressions of $r(t, t + T)$ on $r(t - T, t)$ for return horizons from 1 to 10 years, using the industry portfolio data for the 1926–85 sample period. As predicted by the hypothesis that prices have stationary components, negative slopes are the rule. The bias-adjusted slopes are uniformly negative for return horizons from 2 to 5 years. The unadjusted slopes are almost always negative for all horizons. The slopes reach minimum values for 3–5-year returns, and they become less negative for return horizons beyond 5 years. This U-shaped pattern is consistent with the hypothesis that stock prices also have random-walk components that eventually dominate long-horizon returns. Estimated slopes (not shown) for nominal returns are usually within 0.04 of those for real returns.

The slopes for 3-, 4-, and 5-year returns are large in magnitude and relative to their standard errors. The average values of the bias-adjusted slopes for 3-, 4-, and 5-year returns are -0.30, -0.34, and -0.32; the averages of the unadjusted slopes are -0.38, -0.45, and -0.45. Expression (10b) says that the slope measures the proportion of the variance of T-year returns due to time-varying expected returns generated by slowly decaying stationary price components. The slopes for the industry portfolios thus suggest that these time-varying expected returns average between 30 percent and 45 percent of the variances of 3–5-year returns.

Moreover, the limiting argument for the slopes in Section II says that the variance of the expected change in the stationary price component $z(t)$ approaches half the variance of the long-horizon change in $z(t)$. Thus regression slopes that average between -0.30 and -0.45 estimate that, on average, between 60 percent and 90 percent of the variances of 3–5-year industry returns are due to the stationary price component $z(t)$.

A caveat is in order. The hypothesis that prices contain both random-walk and slowly decaying stationary components predicts a U-shaped pattern of slopes for increasing return horizons. This provides some justification for leaning toward extreme slopes to estimate

TABLE 1

OLS and Bias-adjusted Slopes for Industry Portfolios: 1926–85

$$r(t, t+T) = \alpha(T) + \beta(T)r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)							
	1	2	3	4	5	6	8	10
	OLS Slopes $\beta(T)$							
Food	−.04	−.28*	−.41*	−.46*	−.47*	−.30	−.21	−.20
Apparel	−.11	−.23	−.27	−.37*	−.43*	−.37	−.43	−.56*
Drugs	−.04	−.19	−.25	−.22	−.26	−.22	−.31	−.50
Retail	−.03	−.22	−.37*	−.42*	−.46*	−.34	−.32	−.31
Durables	.00	−.19	−.34*	−.43*	−.43*	−.25	−.20	−.15
Autos	−.07	−.27	−.43*	−.52*	−.48*	−.29*	−.26	−.30
Construction	−.03	−.17	−.34*	−.51*	−.55*	−.36*	−.06	−.04
Finance	−.04	−.22	−.33*	−.35*	−.28	−.09	.00	.06
Miscellaneous	−.04	−.18	−.32*	−.45*	−.50*	−.34	−.22	−.17
Utilities	−.07	−.21	−.35*	−.32*	−.15	.08	−.08	−.18
Transportation	−.12	−.25	−.34*	−.44*	−.45*	−.33	−.30	−.27
Business equipment	−.01	−.26	−.46*	−.51*	−.49*	−.35*	−.17	−.15
Chemicals	−.06	−.38*	−.50*	−.48*	−.50*	−.34*	−.21	−.17
Metal products	−.02	−.25	−.45*	−.59*	−.65*	−.53*	−.38*	−.33*
Metal industries	−.10	−.32*	−.43*	−.46*	−.48*	−.33*	−.04	−.01
Mining	−.11	−.33*	−.44*	−.54*	−.61*	−.44*	−.20	−.21
Oil	−.04	−.28*	−.36*	−.52*	−.53*	−.36*	−.05	−.01
Average $\beta(T)$	−.06	−.25	−.38	−.45	−.45	−.30	−.20	−.21

	Bias-adjusted Slopes $\beta(T)$							
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
Business equipment	.01	−.22	−.39*	−.41*	−.36*	−.19	.05	.13
Chemicals	−.04	−.33*	−.43*	−.38*	−.37*	−.19	.01	.12
Metal products	.01	−.20	−.38*	−.49*	−.52*	−.37*	−.16	−.05
Metal industries	−.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
Average $\beta(T)$	−.03	−.20	−.30	−.34	−.32	−.14	.02	.08
Average $s(\beta)$	.11	.14	.15	.14	.15	.17	.23	.26

Note.—The corrections for the bias of the OLS slopes used in the bias-adjusted slopes are discussed in the Appendix. The standard errors of the slopes are adjusted for the residual autocorrelation due to overlap of monthly observations on longer-horizon returns with the method of Hansen and Hodrick (1980). Averages of the slopes and their standard errors—average $\beta(T)$ and average $s(\beta)$—are computed across the 17 industries. Returns are real (CPI-adjusted).

* Indicates that slope is more than 2.0 standard errors from 0.0.

proportions of return variances due to the two components of prices. Since we do not predict the return horizons likely to produce extreme slopes, however, using the observed extremes to estimate proportions of variance probably overstates the importance of stationary components of prices.

Moreover, a pervasive characteristic of the tests is that small effective sample sizes imply imprecise slope estimates for long-horizon returns. The large standard errors of the industry slopes (averaging 0.11 for 1-year returns and 0.26 for 10-year returns) leave much uncertainty about the true slopes and thus about the proportions of variance due to the random-walk and stationary components of prices. (See the Appendix for pertinent details.)

Deciles

There is no obvious pattern in the variation of the regression slopes across industries. There is a clearer pattern in the slopes for the decile portfolios in table 2. Like the industry slopes, the decile slopes are negative and large for 2–5-year returns. However, the minimum values of the slopes tend to be more extreme for lower (smaller-firm) deciles. All the bias-adjusted slopes less than -0.30 and all the unadjusted slopes less than -0.37 are generated by the equal-weighted market portfolio and deciles 1–7. Most of the 4- and 5-year bias-adjusted slopes for these portfolios are more than 2.0 standard errors below 0.0. The value-weighted market and the larger-firm deciles 9 and 10 produce no bias-adjusted slopes more than 2.0 standard errors below 0.0.

Again, perspective is in order. The large standard errors of the decile slopes—between 0.13 and 0.20 for 3–5-year returns—mean that if stock prices have stationary components, they must generate large negative slopes (and account for large fractions of variance) to be identified reliably, even when the estimates use the entire 1926–85 sample period. Nevertheless, every decile produces a simple OLS slope for 3-, 4-, or 5-year returns more than 2.0 standard errors below 0.0. And the U-shaped pattern of the slopes across return horizons predicted by the hypothesis that prices have both random-walk and slowly decaying stationary components is observed for all the deciles, the industry portfolios, and the two market portfolios.

We conclude that the tests for 1926–85 are consistent with the hypothesis that stock prices have both random-walk and stationary components. The estimates suggest that stationary price components account for large fractions of the variation of returns and that they are relatively more important for small-stock portfolios. We recognize, however, that the imprecision of the tests implies substantial uncertainty about any interpretation of the results. The relevance of this caveat is obvious in the subperiod results that follow.

C. *Subperiod Autocorrelations*

Because the regression slopes are not estimated precisely, the results for the 1926–85 period are in principle the strongest test of the hypothesis that stock prices have stationary components. There are, however, reasons to examine subperiods. First, return variances drop substantially after 1940 (see Officer 1973; French et al. 1987). The variance changes make inference less precise even if the autocorrelations of returns are stationary. Moreover, the high variances of the early years are associated with large price swings. It is possible that the large negative autocorrelations estimated for 1926–85 are a consequence of the early years.

We have estimated the slopes in the regression of $r(t, t + T)$ on $r(t - T, t)$ for the 30-year splits, 1926–55 and 1956–85, and for the longer 1946–85 and 1941–85 periods. The estimates for 1941–85 are in tables 3 and 4. We choose 1941–85 because it is the longest period of roughly constant return variances. The regression slopes it produces are similar in magnitude and pattern to those for 1946–85 and 1956–85.

Like 1926–85, the 1941–85 period produces a general pattern of negative autocorrelation of returns that is consistent with the hypothesis that prices have stationary components. However, the 1941–85 bias-adjusted slopes are typically closer to 0.0, and they do not produce the strong U-shaped pattern across return horizons observed for 1926–85. Moreover, large standard errors (averaging 0.13 for 1-year industry portfolio returns and 0.27 for 8-year returns) make the hypothesis that prices contain no stationary components (the true slopes are 0.0) difficult to reject.

Large standard errors make most hypotheses about subperiods difficult to reject. For example, slope estimates for 1926–55 (not shown) have an even stronger U-shaped pattern than those for 1926–85, while estimates for 1956–85 (also not shown) are much like those for 1941–85. However, the hypothesis that the slopes for 1926–55 and 1956–85 are equal cannot be rejected; indeed, large standard errors make the hypothesis essentially untestable.

In short, the preponderance of negative slopes observed for all periods (shown and not shown) is consistent with the hypothesis that stock prices have stationary components that generate negative autocorrelation in long-horizon returns. Subperiod slopes suggest that the negative autocorrelation is weaker (stationary price components are less important in the variation of returns) after 1940. But reliable

TABLE 2

OLS and Bias-adjusted Slopes for the Decile Portfolios and the Equal- and Value-weighted NYSE Market Portfolios: 1926–85

$$r(t, t+T) = \alpha(T) + \beta(T)r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)							
	1	2	3	4	5	6	8	10
	OLS Slopes $\beta(T)$							
Equal	−.07	−.26	−.39*	−.46*	−.47*	−.29	−.14	−.06
Decile 1	−.01	−.18	−.30	−.46*	−.45*	−.21	.13	.27
Decile 2	−.01	−.16	−.32*	−.51*	−.58*	−.42*	−.24	−.20
Decile 3	−.06	−.20	−.34*	−.46*	−.48*	−.35*	−.30	−.33
Decile 4	−.04	−.23	−.37*	−.48*	−.52*	−.39*	−.30	−.24
Decile 5	−.08	−.27	−.37*	−.42*	−.46*	−.32	−.23	−.16
Decile 6	−.07	−.25	−.38*	−.41*	−.41*	−.26	−.18	−.16
Decile 7	−.09	−.32*	−.42*	−.38*	−.35*	−.18	−.10	−.12
Decile 8	−.08	−.28*	−.37*	−.30*	−.26	−.10	−.07	−.13
Decile 9	−.06	−.26	−.34*	−.24	−.14	.05	.08	−.04
Decile 10	−.08	−.27*	−.35*	−.20	−.08	.09	.12	−.03
Value	−.05	−.24	−.32*	−.19	−.07	.09	.10	−.08
Average	−.06	−.24	−.36	−.39	−.37	−.21	−.11	−.12

	Bias-adjusted Slopes $\beta(T)$							
Equal	−.05	−.22	−.32*	−.36*	−.34*	−.13	.08	.22
Decile 1	.01	−.13	−.23	−.36*	−.32	−.05	.35	.56
Decile 2	.01	−.12	−.25	−.41*	−.45*	−.26	−.02	.09
Decile 3	−.04	−.16	−.27	−.35*	−.35*	−.19	−.08	−.04
Decile 4	−.02	−.19	−.29	−.38*	−.39*	−.23	−.08	.05
Decile 5	−.06	−.23	−.29*	−.32*	−.33*	−.16	−.01	.13
Decile 6	−.05	−.20	−.31*	−.31*	−.28	−.10	.04	.13
Decile 7	−.07	−.27*	−.35*	−.28*	−.22	−.02	.12	.16
Decile 8	−.05	−.23	−.30*	−.20	−.13	.06	.15	.15
Decile 9	−.04	−.21	−.27	−.13	−.01	.21	.30	.25
Decile 10	−.06	−.23	−.27	−.10	.05	.25	.34	.25
Value	−.03	−.20	−.25	−.09	.06	.25	.31	.21
Average	−.04	−.19	−.28	−.28	−.24	−.05	.11	.17
	Standard Errors							
Equal	.11	.14	.14	.13	.14	.17	.24	.28
Value	.11	.14	.15	.16	.20	.23	.34	.43
Average	.11	.14	.15	.14	.16	.19	.25	.31

NOTE.—The corrections for the bias of the OLS slopes used in the bias-adjusted slopes are discussed in the Appendix. The standard errors of the slopes are adjusted for the residual autocorrelation due to overlap of monthly observations on longer-horizon returns with the method of Hansen and Hodrick (1980). Averages of the slopes and their standard errors are computed across the 10 deciles. Returns are real (CPI-adjusted).

* Indicates that the slope is more than 2.0 standard errors from 0.0.

TABLE 3

OLS and Bias-adjusted Slopes for Industry Portfolios: 1941–85

$r(t, t+T) = \alpha(T) + \beta(T) r(t-T, t) + \epsilon(t, t+T)$

	Return Horizon (Years)						
	1	2	3	4	5	6	8
	OLS Slopes $\beta(T)$						
Food	−.03	−.24	−.27	−.26	−.29	−.32	−.43
Apparel	−.08	−.22	−.13	−.14	−.26	−.35	−.51
Drugs	−.02	−.13	−.07	−.01	−.11	−.16	−.30
Retail	−.03	−.21	−.23	−.22	−.32	−.34	−.41
Durables	−.03	−.26	−.30	−.27	−.24	−.22	−.24
Autos	−.06	−.36*	−.39*	−.35	−.33*	−.29	−.33
Construction	−.06	−.23	−.24	−.29	−.31	−.28	−.10
Finance	−.02	−.11	−.10	−.12	−.14	−.08	.05
Miscellaneous	.00	−.18	−.23	−.27	−.34	−.34	−.29
Utilities	−.03	−.18	−.30	−.21	−.12	.01	−.05
Transportation	−.10	−.20	−.25	−.33	−.40*	−.42*	−.29
Business equipment	−.10	−.26	−.24	−.28	−.35	−.33	−.18
Chemicals	−.25*	−.47*	−.32*	−.22	−.22	−.24	−.21
Metal products	−.06	−.29	−.39*	−.44*	−.49*	−.49*	−.40
Metal industries	−.19	−.26	−.22	−.19	−.21	−.18	.00
Mining	−.18	−.36*	−.41*	−.46*	−.54*	−.51*	−.32
Oil	−.17	−.27	−.25	−.33	−.32	−.32	−.12
Average $\beta(T)$	−.08	−.25	−.26	−.26	−.29	−.29	−.24

	Bias-adjusted Slopes $\beta(T)$						
Food	.00	−.18	−.17	−.13	−.13	−.13	−.17
Apparel	−.05	−.16	−.04	−.02	−.10	−.16	−.26
Drugs	.01	−.06	.03	.12	.05	.03	−.04
Retail	.00	−.15	−.13	−.09	−.16	−.15	−.16
Durables	.00	−.20	−.20	−.14	−.09	−.03	.01
Autos	−.03	−.30	−.30	−.22	−.17	−.10	−.07
Construction	−.03	−.17	−.15	−.16	−.16	−.09	.15
Finance	.01	−.04	−.00	.00	.02	.11	.30
Miscellaneous	.03	−.12	−.13	−.14	−.18	−.14	−.03
Utilities	.00	−.12	−.21	−.08	.04	.20	.21
Transportation	−.07	−.13	−.16	−.21	−.24	−.23	−.04
Business equipment	−.07	−.20	−.15	−.15	−.19	−.14	.08
Chemicals	−.22	−.41*	−.22	−.09	−.06	−.05	.05
Metal products	−.03	−.22	−.29	−.31	−.33*	−.30	−.15
Metal industries	−.16	−.20	−.12	−.06	−.05	.01	.25
Mining	−.15	−.30*	−.31	−.33	−.39*	−.32	−.06
Oil	−.14	−.21	−.16	−.20	−.16	−.12	.13
Average $\beta(T)$	−.05	−.19	−.16	−.13	−.14	−.09	.01
Average $s(\beta)$	.13	.16	.19	.20	.21	.23	.27

NOTE.—The corrections for the bias of the OLS slopes used in the bias-adjusted slopes are discussed in the Appendix. The standard errors of the slopes are adjusted for the residual autocorrelation due to overlap of monthly observations on longer-horizon returns with the method of Hansen and Hodrick (1980). Averages of the slopes and their standard errors—average $\beta(T)$ and average $s(\beta)$—are computed across the 17 industries. Returns are real (CPI-adjusted).

* Indicates that the slope is more than 2.0 standard errors from 0.0.

TABLE 4

OLS and Bias-adjusted Slopes for the Decile Portfolios and the Equal- and Value-weighted NYSE Market Portfolios: 1941–85

$$r(t, t+T) = \alpha(T) + \beta(T)r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)						
	1	2	3	4	5	6	8
	OLS Slopes $\beta(T)$						
Equal	−.09	−.24	−.23	−.22	−.26	−.24	−.18
Decile 1	.02	−.05	−.13	−.29	−.36*	−.30	−.15
Decile 2	.00	−.14	−.22	−.33*	−.44*	−.48	−.42
Decile 3	−.05	−.22	−.24	−.27	−.33	−.36	−.39
Decile 4	−.05	−.24	−.26	−.31	−.39	−.42	−.36
Decile 5	−.08	−.27	−.24	−.18	−.26	−.29	−.26
Decile 6	−.06	−.23	−.22	−.17	−.22	−.22	−.19
Decile 7	−.13	−.32*	−.23	−.11	−.11	−.10	−.10
Decile 8	−.15	−.31*	−.21	−.04	−.06	−.05	−.13
Decile 9	−.10	−.19	−.05	.13	.15	.15	.10
Decile 10	−.12	−.23	−.04	.22	.26	.22	.15
Value	−.09	−.22	−.03	.19	.22	.18	.09
Average	−.07	−.22	−.18	−.14	−.17	−.18	−.17

	Bias-adjusted Slopes $\beta(T)$						
Equal	−.06	−.18	−.13	−.09	−.10	−.05	.08
Decile 1	.05	.01	−.03	−.16	−.20	−.11	.11
Decile 2	.03	−.08	−.12	−.21	−.28	−.28	−.17
Decile 3	−.02	−.16	−.15	−.14	−.17	−.17	−.13
Decile 4	−.02	−.17	−.17	−.18	−.23	−.22	−.11
Decile 5	−.05	−.21	−.15	−.06	−.10	−.10	−.01
Decile 6	−.03	−.17	−.13	−.04	−.06	−.03	.07
Decile 7	−.10	−.26	−.14	.02	.05	.09	.16
Decile 8	−.12	−.25	−.11	.09	.10	.14	.12
Decile 9	−.07	−.12	.04	.26	.31	.35	.35
Decile 10	−.09	−.17	.05	.34	.42	.41	.41
Value	−.06	−.16	.06	.32	.38	.37	.35
Average	−.04	−.16	−.09	−.01	−.02	.01	.08
	Standard Errors						
Equal	.13	.16	.19	.21	.21	.24	.29
Value	.13	.16	.19	.23	.27	.31	.41
Average	.13	.16	.19	.21	.22	.25	.30

NOTE.—The corrections for the bias of the OLS slopes used in the bias-adjusted slopes are discussed in the Appendix. The standard errors of the slopes are adjusted for the residual autocorrelation due to overlap of monthly observations on longer-horizon returns with the method of Hansen and Hodrick (1980). Averages of the slopes and their standard errors are computed across the 10 deciles. Returns are real (CPI-adjusted).

* Indicates that the slope is more than 2.0 standard errors from 0.0.

contrasts across periods are impossible. Perhaps stationary price components are less important after 1940. Perhaps prices no longer have such temporary components. Only time (and lots of it) will tell.[2]

IV. Negative Autocorrelation: Common or Firm-specific Factors?

An important economic question is whether the negative autocorrelation of long-horizon returns is due to common or firm-specific factors. Evidence that the autocorrelation is due to common factors would raise the possibility that it can be traced to common macroeconomic driving variables. On the other hand, evidence that the autocorrelation is firm-specific would raise the possibility that expected returns have firm-specific components. Such a finding would challenge the relevance of parsimonious equilibrium pricing models. We summarize briefly some preliminary work on these issues.

A. *Portfolios*

Evidence that a single portfolio absorbs the negative autocorrelation of returns for all the industry and decile portfolios would suggest that the negative autocorrelation of the 1926–85 period is due to one common factor. We have estimated residual autocorrelations for regressions of the decile and industry portfolio returns on the return to decile 1. We choose decile 1 as the explanatory portfolio because of the evidence in table 2 that the general negative autocorrelation of portfolio returns is a larger fraction of the variation of returns on portfolios of small firms.

For the 1926–85 period, the residual autocorrelations for the industry and decile portfolios are more often positive than negative, but they are typically close to 0.0. Results for other periods are similar. The evidence suggests that the general negative autocorrelation of portfolio returns is largely due to a common macroeconomic phenomenon.

[2] We have also tested the autocorrelation of returns by examining return variances for increasing horizons (see Alexander 1961; Cochrane 1986; French and Roll 1986; Lo and MacKinlay 1986). Return variances for the industry and decile portfolios behave as predicted by the hypothesis that stock prices have stationary components that induce negative autocorrelation in returns. In particular, the variances grow less than in proportion to the return horizon. Unlike the regression slopes in tables 1 and 2, however, the variance tests for the 1926–85 period do not reliably identify negative autocorrelation in long-horizon returns. We mention the variance tests to emphasize that different univariate approaches to identifying slowly decaying stationary components of price have the common problem of low statistical power—a point treated in detail in Poterba and Summers (1987).

B. *Individual Securities*

Since the decile and industry portfolios are diversified, firm-specific factors contribute little to the variation of their returns. Tests for autocorrelation due to firm-specific factors must use individual stocks. A problem, however, is that reliable inferences about long-horizon returns require long sample periods, but the population of NYSE stocks changes through time. Our preliminary solution is to study the 82 stocks listed for the entire 1926–85 period.

The equal-weighted portfolio of the 82 stocks produces a strong U-shaped pattern of autocorrelations like that observed for the equal-weighted portfolio of all stocks in table 2. The bias-adjusted autocorrelations for 2-, 3-, and 4-year returns on this portfolio are -0.26, -0.36, and -0.28, and they are at least 1.99 standard errors below 0.0. The autocorrelation of returns on the 82 individual stocks is weaker. The averages of the (82) 2-, 3-, and 4-year bias-adjusted slopes are -0.10, -0.16, and -0.10, and the slopes are, on average, -0.78, -1.09, and -0.76 standard errors from 0.0. Moreover, even the weak negative autocorrelation in the individual stock returns disappears in the residuals from regressions of the returns on decile 1. The average bias-adjusted residual autocorrelations for the 82 stocks are close to 0.0 for all return horizons, and the cross-sectional distributions of the autocorrelations are roughly symmetric about 0.0. Tests on the 230 stocks listed for the 1941–85 period yield similar results.

Heavy-handed conclusions from these rather special samples of survivors are inappropriate. But the fact that returns on portfolios of the survivors have autocorrelations similar to those of the equal-weighted market portfolio gives some confidence in the individual stock evidence that firm-specific components of long-horizon stock returns have no autocorrelation. The results are heartening for proponents of parsimonious equilibrium pricing models.

V. Conclusions

First-order autocorrelations of industry and decile portfolio returns for the 1926–85 period form a U-shaped pattern across increasing return horizons. The autocorrelations become negative for 2-year returns, reach minimum values for 3–5-year returns, and then move back toward 0.0 for longer return horizons. This pattern is consistent with the hypothesis that stock prices have a slowly decaying stationary component. The negative autocorrelation of returns generated by a slowly decaying component of prices is weak at the short return horizons common in empirical work, but it becomes stronger as the return horizon increases. Eventually, however, random-walk price components begin to dominate the variation of returns, and long-horizon autocorrelations move back toward 0.0.

Autocorrelation may reflect market inefficiency or time-varying equilibrium expected returns generated by rational investor behavior. Neither view suggests, however, that patterns of autocorrelation should be stable for a sample period as long as 60 years. Although a tendency toward negative autocorrelation of long-horizon returns is always observed, subperiod results suggest that the strong negative autocorrelation of the 1926–85 period may be largely due to the first 15 years. Autocorrelations for periods after 1940 are closer to 0.0, and they do not show the U-shaped pattern of the overall period. Because sample sizes for long-horizon returns are small, however, sample autocorrelations cannot identify changes in the time-series properties of returns. Stationary price components may be less important after 1940, or perhaps prices no longer have such temporary components. Resolution of this issue will require more powerful statistical techniques.

Appendix

Simulations

The simulations mimic properties of NYSE returns. Monthly simulated returns are summed to get overlapping monthly observations on T-year returns, $r(t, t + T)$. We estimate regressions of simulated returns $r(t, t + T)$ on lagged returns $r(t, t - T)$ to obtain sampling distributions of the slopes. The simulations use 720 observations per replication, matching the number of months in the 1926–85 sample period.

We simulate two models in which the true slopes are 0.0. One is a random walk in the log price with normal (0, 1) monthly returns. The second is a random walk in which return variances change every 2 years to approximate changes in stock return variances (see table A1). We also simulate constant and changing variance versions of the model (1)–(3) in which the log price has both a random-walk and an AR1 component (see table A2).

A. *The Random-Walk Simulations*

Table A1 summarizes estimates of regression slopes for the random-walk models. The negative bias of OLS slopes is apparent from the average slopes in the first line of the table. The bias increases with the return horizon because effective sample sizes are smaller for longer horizons and because the increased overlap of the observations increases serial dependence.

The second line of the table shows average bias-adjusted slopes. The bias correction is the average slope for each return horizon from 10,000 preliminary replications of the constant-variance random-walk model. These bias corrections are used whenever we refer to bias-adjusted slopes for the 1926–85 period for NYSE returns or for the simulations. Since the average bias-adjusted slopes in table A1 are close to 0.0, the preliminary simulations give good estimates of bias when monthly returns are white noise. The bias corrections for the 1941–85 period (540 months) used in the text are also average slopes from 10,000 preliminary replications of the random-walk model, but with 540 rather than 720 observations per replication.

The standard deviation of the sample of slopes for each return horizon in table A1 estimates the standard error of the slope. The standard deviations are large, for example, 0.24 for 5-year returns. Since 720 months yield 12 nonoverlapping 5-year returns, the slope standard error for nonoverlapping returns would be $(1/11)^{.5} = 0.30$. The standard error 0.24 for 600 monthly observations on 5-year returns implies an effective sample size of 18.4 nonoverlapping returns.

The t's in table A1 for tests of bias-adjusted slopes against 0.0 use standard errors adjusted for residual autocorrelation due to return overlap (see Hansen and Hodrick 1980). Lower fractiles of the t's are estimates of critical values for tests of the hypothesis that the slope is 0.0 (prices are random walks) against the alternative that the slope is negative because the price has a temporary component. The t's for the changing-variance random walk are most relevant, given the changing variances of stock returns. For 3–5-year returns, the .10, .05, and .01 fractiles of the t's are around -1.8, -2.3, and -3.5. These are more extreme than the same fractiles of the unit normal, -1.28, -1.65, and -2.33. Standard deviations around 1.3 also show that the simulation t's have more dispersion than the unit normal.

Comparison with part A of table A1 shows that the higher dispersion of the t's in part B is due to changing variances. We have estimated slope standard errors using the method of White (1980) and Hansen (1982) to jointly correct for autocorrelation and heteroscedasticity. Resulting t's show more dispersion and more extreme negative lower fractiles than t's based on Hansen and Hodrick's (1980) standard errors. In the NYSE returns, we use Hansen and Hodrick's standard errors.

B. The Mixed AR1–Random-Walk Simulations

Table A2 summarizes simulations of the mixed AR1–random-walk model. True slopes that drop from -0.10 for 1-year returns to -0.27 for 5-year returns are similar to the slopes estimated for the value-weighted NYSE market portfolio in table 1. We view the simulations as evidence about the power of the tests to reject the random-walk model when prices have stationary components that imply slopes in the 3–5-year range like those observed for NYSE returns.

Under the random-walk hypothesis, t's for tests of bias-adjusted slopes against 0.0 are relevant. Average t's in part B of table A2 are only around -1.18 for 3–5-year returns. Likewise, the fractiles of the slopes for the mixed AR1–random-walk model in part B of table A2 are somewhat to the left of those for the random-walk model in part B of table A1, but the overlap of the distributions is substantial. In short, large standard errors for the slopes (the standard deviation of the 5-year slopes in pt. B of table A2 is 0.18) mean that the regression tests have little power to reject the random-walk model when prices have a stationary component that accounts for 27 percent of the variance of 5-year returns. Stationary components of stock prices must generate large negative slopes to be identified reliably in our tests.

Finally, consistent with Kendall (1954) and Marriot and Pope (1954), table

TABLE A1

SUMMARY OF SIMULATIONS WHEN PRICES ARE PURE RANDOM WALKS

$$r(t, t+T) = \alpha + \beta r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)							
	1	2	3	4	5	6	8	10
	A. $\epsilon(t, t+T)$ Homoscedastic (Constant Variance): Mean and Standard Deviation of β (OLS and Bias-adjusted)							
$\bar{\beta}$ (OLS)	−.03	−.04	−.07	−.10	−.13	−.16	−.24	−.30
$\bar{\beta}$ (adjusted)	−.01	.00	.00	.00	.00	.00	−.02	−.01
$s(\beta)$	.11	.15	.19	.22	.24	.26	.28	.30
	Mean, Standard Deviation, and Fractiles of t's for Test of Bias-adjusted β = 0.0							
Mean	−.09	−.01	−.03	−.05	−.09	−.12	−.25	−.23
Standard deviation	1.06	1.00	1.09	1.12	1.13	1.10	1.10	1.12
Fractile:								
.01	−2.62	−2.56	−2.78	−2.93	−2.85	−2.65	−2.76	−4.04
.05	−2.12	−1.51	−1.81	−2.04	−1.95	−2.00	−2.07	−1.92
.10	−1.56	−1.24	−1.42	−1.50	−1.56	−1.58	−1.66	−1.53
.25	−.78	−.76	−.74	−.76	−.83	−.88	−1.03	−.87

	B. $\epsilon(t, t + T)$ HETEROSCEDASTIC (Changing Variance): Mean and Standard Deviation of β (OLS and Bias-adjusted); Fractiles (Bias-adjusted)							
$\bar{\beta}$ (OLS)	−.01	−.05	−.08	−.10	−.11	−.13	−.11	−.11
$\bar{\beta}$ (adjusted)	.01	−.00	−.01	.00	.02	.03	.11	.17
$s(\beta)$	.15	.19	.20	.22	.23	.25	.25	.28
Fractile:								
.01	−.27	−.45	−.43	−.48	−.47	−.45	−.43	−.40
.05	−.24	−.31	−.34	−.35	−.35	−.34	−.30	−.24
.10	−.19	−.23	−.27	−.28	−.28	−.28	−.20	−.19
.25	−.10	−.14	−.16	−.16	−.15	−.17	−.08	−.02
.50	.00	−.02	.00	.00	.00	.01	.08	.12
.75	.10	.14	.14	.16	.18	.21	.26	.30
.90	.19	.26	.25	.28	.34	.37	.44	.56
.95	.24	.33	.32	.35	.42	.45	.53	.70
.99	.38	.44	.48	.53	.54	.60	.69	.90
	Mean, Standard Deviation, and Fractiles of t's for Test of Bias-adjusted β = 0.0							
Mean	.01	−.09	−.12	−.10	−.03	.05	.50	.84
Standard deviation	1.43	1.39	1.24	1.31	1.37	1.45	1.51	1.61
Fractile:								
.01	−2.87	−3.77	−3.29	−3.51	−3.62	−3.22	−3.40	−2.56
.05	−2.39	−2.53	−2.30	−2.48	−2.30	−2.25	−1.67	−1.21
.10	−1.90	−1.75	−1.78	−1.74	−1.83	−1.81	−1.13	−.84
.25	−1.02	−.99	−.96	−.88	−.83	−.91	−.38	−.10

NOTE.—The number of monthly returns per replication is 720. Monthly returns are summed to get overlapping monthly observations on T-year returns, $r(t, t + T)$, $T = 1, 2, \ldots, 10$. Sampling distributions of the slopes are based on 200 replications for the 1-, 2-, 8-, and 10-year regressions and 1,000 for the 3–6-year regressions. The log price in pt. A is a random walk with normal (0, 1) monthly returns. The log price in pt. B is a heteroscedastic random walk that changes the standard deviation of the white-noise returns every 2 years to approximate variation through time in stock return variances. Specifically, in each replication, the normal (0, 1) monthly returns in nonoverlapping 2-year periods, generated for the homoscedastic random walk, are multiplied by the standard deviation of the monthly returns on the equal-weighted NYSE market portfolio for the corresponding 2-year period.

TABLE A2

SUMMARY OF SIMULATIONS WHEN PRICES HAVE AR1 AND RANDOM-WALK COMPONENTS

$$r(t, t+T) = \alpha + \beta r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)							
	1	2	3	4	5	6	8	10
	A. $\epsilon(t, t+T)$ Homoscedastic (Constant Variance)							
β (true)	−.10	−.17	−.22	−.25	−.27	−.27	−.28	−.27
	Mean and Standard Deviation of β (OLS and Bias-adjusted)							
$\overline{\beta}$ (OLS)	−.12	−.20	−.24	−.28	−.31	−.33	−.36	−.38
$\overline{\beta}$ (adjusted)	−.10	−.15	−.17	−.18	−.18	−.17	−.14	−.10
$s(\beta)$	.10	.11	.15	.16	.18	.19	.22	.23
	Mean and Standard Deviation of t's for Test of OLS or Bias-adjusted $\beta = 0.0$							
Mean (OLS)	−1.22	−1.55	−1.59	−1.64	−1.66	−1.71	−1.82	−1.77
Standard deviation	.99	.92	1.08	1.10	1.13	1.14	1.41	1.37
Mean (adjusted)	−1.04	−1.21	−.92	−1.08	−1.00	−.90	−.84	−.58
Standard deviation	.99	.90	1.04	1.04	1.05	1.03	1.20	1.10
	B. $\epsilon(t, t+T)$ Heteroscedastic (Changing Variance)							
β (true)	−.10	−.17	−.22	−.25	−.27	−.27	−.28	−.27

	Mean and Standard Deviation of β (OLS and Bias-adjusted); Fractiles (Bias-adjusted)							
$\bar{\beta}$ (OLS)	−.12	−.19	−.24	−.27	−.30	−.31	−.30	−.28
$\underline{\beta}$ (adjusted)	−.10	−.14	−.17	−.17	−.17	−.15	−.08	.01
$s(\beta)$	.14	.16	.17	.17	.18	.19	.22	.23
Fractile:								
.01	−.44	−.51	−.51	−.51	−.52	−.52	−.55	−.48
.05	−.34	−.40	−.43	−.44	−.45	−.44	−.41	−.34
.10	−.27	−.34	−.37	−.39	−.39	−.38	−.34	−.28
.25	−.19	−.26	−.28	−.29	−.29	−.29	−.23	−.18
.50	−.10	−.14	−.17	−.18	−.18	−.17	−.13	−.03
.75	−.01	−.04	−.04	−.06	−.06	−.03	.03	.10
.90	.10	.07	.06	.06	.07	.08	.18	.30
.95	.14	.13	.12	.12	.13	.18	.34	.40
.99	.18	.21	.25	.25	.27	.32	.44	.55
	Mean and Standard Deviation of *t*'s for Test of OLS or Bias-adjusted β = 0.0							
Mean (OLS)	−1.23	−1.54	−1.62	−1.80	−1.96	−2.01	−1.82	−1.74
Standard deviation	1.50	1.33	1.30	1.31	1.37	1.47	1.42	1.51
Mean (adjusted)	−1.04	−1.19	−1.14	−1.18	−1.17	−1.06	−.58	−.13
Standard deviation	1.49	1.30	1.24	1.23	1.24	1.30	1.28	1.34
	Mean and Standard Deviation of *t*'s for Test of OLS or Bias-adjusted β = −0.5							
Mean (OLS)	3.74	2.17	1.59	1.29	1.11	1.03	1.13	1.28
Standard deviation	1.19	1.00	.95	.95	1.00	1.09	1.24	1.40
Mean (adjusted)	3.93	2.52	2.08	1.91	1.90	1.98	2.36	2.89
Standard deviation	1.18	.98	.91	.91	.97	1.10	1.33	1.68

NOTE.—The AR1 parameter for the stationary component of the simulated monthly returns is .975, the monthly AR1 and random-walk shocks are independent, and the AR1 shock has twice the standard deviation of the random-walk shock. The model in pt. B is a heteroscedastic version of the model in pt. A, in which the standard deviations of both the random-walk and AR1 shocks change within each replication, as described for the second random-walk model in table A1.

A2 shows that simple OLS slopes are less biased when the true slopes are negative, and bias corrections relevant when the true slopes are 0.0 produce estimates biased toward 0.0. For example, the true 5-year slope in part B of table A2 is -0.27, the average of simple OLS slopes is -0.30, and the average bias-adjusted slope is -0.17. Thus simple OLS slopes are closer to unbiased when the log price has an important AR1 component.

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