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ABSTRACT

In both corporate finance and asset pricing empirical work, researchers are often confronted with panel data. In these data sets, the residuals may be correlated across firms and across time, and OLS standard errors can be biased. Historically, the two literatures have used different solutions to this problem. Corporate finance has relied on Rogers standard errors, while asset pricing has used the Fama-MacBeth procedure to estimate standard errors. This paper will examine the different methods used in the literature and explain when the different methods yield the same (and correct) standard errors and when they diverge. The intent is to provide intuition as to why the different approaches sometimes give different answers and give researchers guidance for their use.

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I) Introduction

It is well known that OLS standard errors are correct when the residuals are independent and identically distributed. When the residuals are correlated across observations, OLS standard errors can be biased and either over or underestimate the true variability of the coefficient estimates. Although the use of panel data sets (e.g. data sets that contain observations on multiple firms in multiple years) is common, the way that researchers have addressed possible biases in the standard errors varies widely. In recently published finance papers which include a regression on panel data, forty-three percent of the papers did not report adjusting the standard errors for possible dependence in the residuals.[1] Approaches for estimating the coefficients and standard errors in the presence of within cluster correlation varied among the remaining papers. 34 percent of the papers estimated both the coefficients and the standard errors using the Fama-MacBeth procedure (Fama-MacBeth, 1973). 28 percent of the papers included dummy variables for each cluster (e.g. for each firm). The remaining two methods used OLS (or an analogous method) to estimate the coefficients but reported standard errors adjusted for correlation within a cluster. Eight percent of the papers adjusted the standard errors using the Newey-West procedure (Newey and West, 1987) modified for use in a panel data set, while 23 percent of the papers reported Rogers standard errors (Williams, 2000, Rogers, 1993, Moulton, 1990, Moulton, 1986) which are White standard errors adjusted to account for possible correlation within a cluster. These are also called clustered standard errors.

[1] I searched papers published in the *Journal of Finance*, the *Journal of Financial Economics*, and the *Review of Financial Studies* in the years 2001- 2004 for a description of how the coefficients and standard errors were estimated in a panel data set. I included both standard linear regressions as well as non-linear estimation techniques such as logits and tobits in my survey. Panel data sets are data sets where observations can be grouped into clusters (e.g. multiple observations per firm, per industry, per year, or per country). I included only papers which reported at least five observations in each dimension (e.g. firms and years). 207 papers met the selection criteria. Papers which did not report the method for estimating the standard errors, or reported correcting the standard errors only for heteroscedasticity (i.e. White standard errors which are not robust to within cluster dependence), were coded as not having corrected the standard errors for within cluster dependence. Where the paper's description was ambiguous, I contacted the authors.

Although the literature has used a diversity of methods to estimate standard errors in panel data sets, it has provided little guidance to researchers as to when a given method is appropriate. Since the methods can sometimes produce different estimates it is important to understand how the methods compare, when they will produce different estimates of the standard errors, and when they differ how should researchers choose among the estimates. This is the paper's objective.

There are two general forms of dependence which are most common in finance applications. They will serve as the basis for the analysis. The residuals of a given firm may be correlated across years (time series dependence). I will call this a firm effect. Alternatively, the residuals of a given year may be correlated across firms (cross-sectional dependence). I will call this a time effect. I will simulate panel data set with both forms of dependence, first individually and then jointly. With the simulated data, I can estimate the coefficients and standard errors using each of the methods and compare their performance. Section II contains the standard error estimates in the presence of a fixed firm effect. Both the OLS and the Fama-MacBeth standard errors are biased downward and the magnitude of this bias is increasing in the size of the firm effect. The Rogers standard errors are unbiased as they account for the dependence created by the firm effect. The Newey-West standard errors, as modified for panel data, are also biased but their bias is small.

In section III, the same analysis is conducted with a time effect instead of a firm effect. Since the Fama-MacBeth procedure is designed to address a time effect, not a firm effect, the Fama-MacBeth standard errors are unbiased and the coefficient estimates are more efficient than the OLS estimates. The intuition of these first two sections carries over to Section IV, were I simulate data with both a firm and a time effect. Thus far, the firm effect has been specified as a constant effect (e.g. does not decay over time). In practice, the firm effect may decay over time and so the correlation between residuals declines as the time between them grows. In Section V, I simulate data with a more general correlation structure. This not only allows me to compare OLS, Rogers, and Fama-MacBeth standard errors in a more general setting, it also allows me to access the relative benefit of using fixed effects (firm dummies) to estimate the coefficients and whether this changes the way researchers should estimate standard errors. Most papers do not report standard errors estimated by multiple methods. Thus in Section VI, I apply the various estimation techniques to two real data sets and compare their relative performance. This allows me to provide guidance as to which technique should be used in actual situations. It allows me to show how differences in standard error estimates (e.g. White versus Rogers standard error) can provide information about the deficiency in a model and directions for improving them.

II) Estimating Standard Errors in the Presence of a Fixed Firm Effect.

A) Rogers Standard Error Estimates.

To provide intuition on why the standard errors produced by OLS are incorrect and how Rogers standard errors correct this problem, it is helpful to briefly review the expression for the variance of the estimated coefficients. The standard regression for a panel data set is:

$$Y_{it} = X_{it}\,\beta + \varepsilon_{it} \tag{1}$$

where we have observations on firms (i) across years (t). X and ε are assumed to be independent of each other and to have a zero mean. The zero mean is without loss of generality and allows us to ignore the intercepts and calculate the variances as sums of the squares of the variable. The estimated coefficient is:

$$
\begin{aligned}
\hat{\beta}_{OLS} &= \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it} \, Y_{it}}{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2} = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it} \, (X_{it} \, \beta + \varepsilon_{it})}{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2} \\
&= \beta + \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it} \, \varepsilon_{it}}{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2}
\end{aligned} \tag{2}
$$

and the variance of the coefficient is:

$$
\begin{aligned}
\operatorname{Var}[\, \hat{\beta}_{OLS} - \beta \,] &= \operatorname{plim}\left[\left(\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it} \, \varepsilon_{it} \right)^2 \left(\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2 \right)^{-2} \right] \\
&= \operatorname{plim}\left[\left(\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2 \, \varepsilon_{it}^2 \right) \left(\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^2 \right)^{-2} \right] \\
&= NT \, \sigma_X^2 \, \sigma_\varepsilon^2 \, (NT \, \sigma_X^2)^{-2} \\
&= \frac{\sigma_\varepsilon^2}{NT \, \sigma_X^2}
\end{aligned} \tag{3}
$$

This is the standard OLS formula and is based on the assumption that the errors are independent and identically distributed (Green, 2000). The independence assumption is used to move from the first to the second line in equation (3) (i.e., the covariance between residuals is zero). The assumption of an identical distribution (e.g., homoscedastic errors) is used to move from the second to the third line.[2] It is the independence assumption which is often violated in panel data and which is the focus of the paper.

In relaxing the assumption of independent errors, I initially assume the data has a fixed firm

[2] The Rogers standard errors are robust to heteroscedastic residuals. However, since this is not my focus, I assume that the errors are homoscedastic in the equations and simulations. I use White standard errors as my baseline estimates when analyzing actual data in section VI, since the residuals are not homoscedastic in either data set.

effect. Thus the residuals consist of a firm specific component (γ_i) as well as a component which is unique to each observation (η_{it}). The residuals can be specified as:

$$\varepsilon_{it} = \gamma_i + \eta_{it} \tag{4}$$

Assume that the independent variable X also has a firm specific component.

$$X_{it} = \mu_i + \nu_{it} \tag{5}$$

Each of the components of X (μ and ν) and ε (γ and η) are independent of each other. This is necessary for the coefficient estimates to be consistent.[3] This is a typical panel data structure and implies a specific correlation among the observations of a given firm. Both the independent variable and the residual are correlated across two observations of the same firm, but are independent across firms.

$$\begin{aligned}
\operatorname{corr}(X_{it}, X_{js}) &= 1 && \text{for } i=j \text{ and } t = s \\
&= \rho_X = \sigma_\mu^2 / \sigma_X^2 && \text{for } i=j \text{ and all } t \neq s \\
&= 0 && \text{for all } i \neq j \\
\operatorname{corr}(\varepsilon_{it}, \varepsilon_{js}) &= 1 && \text{for } i=j \text{ and } t = s \\
&= \rho_\varepsilon = \sigma_\gamma^2 / \sigma_\varepsilon^2 && \text{for } i=j \text{ and all } t \neq s \\
&= 0 && \text{for all } i \neq j
\end{aligned} \tag{6}$$

Given this data structure [equations (1), (4), and (5)], I can calculate the true standard error of the OLS coefficient. Since the residuals are no longer independent within cluster, the square of the summed residuals is no longer equal to the sum of the squared residuals. The same statement can be made about the independent variable. The co-variances must be included as well. The variance

[3] I am assuming that the model is correctly specified. I do this to focus on estimating the standard errors. In actual data sets, this assumption would need to be tested.

of the OLS coefficient estimate is now:

$$\begin{aligned}
\mathrm{Var}[\,\hat{\beta}_{OLS} - \beta\,] &= \mathrm{plim}\left[\left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}\ \varepsilon_{it}\right)^2 \left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}^2\right)^{-2}\right] \\
&= \mathrm{plim}\left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}\ \varepsilon_{it}\right)^2 \left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}^2\right)^{-2}\right] \\
&= \mathrm{plim}\left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}^2\,\varepsilon_{it}^2 + 2\sum_{t=1}^{T-1}\sum_{s=t+1}^{T} X_{it}\,X_{is}\,\varepsilon_{it}\,\varepsilon_{is}\right)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}^2\right)^{-2}\right] \qquad \textbf{(7)} \\
&= \left(N\ T\ \sigma_X^2\ \sigma_e^2 + N\ T\ (T-1)\ \rho_x\ \sigma_X^2\ \rho_e\ \sigma_e^2\right)\left(NT\,\sigma_X^2\right)^{-2} \\
&= \frac{\sigma_\varepsilon^2}{NT\ \sigma_X^2}\left(1 + (T-1)\ \rho_X\ \rho_\varepsilon\right)
\end{aligned}$$

I used the assumption that residuals are independent across firms [e.g. $i \neq j$, see equation (6)] in deriving the second line. Given the assumed data structure, the within cluster correlations of both X and ε are positive and are equal to the fraction of the variance which is attributable to the fixed firm effect. When the data have a fixed firm effect, the OLS standard errors will always understate the true standard error if and only if both ρ_X or ρ_ε are non-zero.[4] The magnitude of the error is also increasing in the number of years in the data set (see Bertrand, Duflo, and Mullainathan, 2004). To understand this intuition, consider the extreme case where the independent variables and residuals

[4] If the firm effect is not fixed, the correlation of ε_t and ε_{t-k} is a non-trivial function of k. In this case, the equation is a sum of the correlations between ε_t and ε_{t-k} times the correlation between X_t and X_{t-k}, for all k<T. When the correlations are not constant, the variance of the coefficient estimate is:

$$\mathrm{Var}[\,\hat{\beta}_{OLS} - \beta\,] = \frac{\sigma_\varepsilon^2}{NT\ \sigma_X^2}\left(1 + \frac{2}{T}\sum_{k=1}^{T}(T-k)\,\rho_{x,k}\,\rho_{\varepsilon,k}\right)$$

When the auto-correlations vary, they can be positive or negative. It is thus possible for the OLS standard error to under or over-estimate the true standard error. I will address auto-correlations which decline as the lag length (k) increases in Section V, when I examine non-fixed firm effects. Finally, if the panel is unbalanced (different T for each i), the true standard error and the bias in the OLS standard errors is even larger than equation (7) (see Moulton, 1986).

are perfectly correlated across time (i.e. $\rho_X = 1$ and $\rho_\varepsilon = 1$). In this case, each additional year provides no additional information and will have no effect on the true standard error. However, the OLS standard errors will assume each additional year provides N additional observations and the estimated standard error will shrink accordingly and incorrectly.

The correlation of the residuals within cluster is the problem the Rogers standard errors (White standard errors adjusted for clustering) are designed to correct.[5] By squaring the sum of $X_{it}\varepsilon_{it}$ within each cluster, the covariance between residuals within cluster is estimated (see Figure 1). This correlation can be of any form; no parametric structure is assumed. However, the squared sum of $X_{it}\varepsilon_{it}$ is assumed to have the same distribution across the clusters. Thus these standard errors are consistent as the number of clusters grows (Donald and Lang, 2001; and Wooldridge, 2002). We return to this issue in Section III.

B) Testing the Standard Error Estimates by Simulation.

I simulated a panel data set and then estimated the slope coefficient and its standard error. By doing this multiple times we can observe the true standard error as well as the average estimated standard errors.[6] In the first version of the simulation, I included a fixed firm effect but no time effect in the independent variable and the residual. Thus the data are simulated as described in

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[5] The exact formula for the Rogers standard error is:

$$S^2(\beta) = \frac{N\,(NT-1)\,\sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}\,\varepsilon_{it}\right)^2}{(NT-k)\,(N-1)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}^2\right)^2}$$

[6] Each simulated data set contains 10 yearly observations on 500 firms and thus 5,000 observations. The components of the independent variable and the residual are assumed to be independent and normally distributed with zero means. For each data set, I estimated the coefficients and standard errors using each method described below. The reported means and standard deviations reported in the tables are based on 5,000 simulations.

equations (4) and (5). Across simulations I assumed that the standard deviation of the independent variable and the residual are both constant at one and two respectively. This will produce an R^2 of 20 percent which is not unusual for empirical finance regressions. Across different simulations, I altered the fraction of the variance in the independent variable which is due to the firm effect. This fraction ranges from zero to seventy-five percent in twenty-five percent increments (see Table 1). I did the same for the residual. This allows me to demonstrate how the magnitude of the bias in the OLS standard errors varies with the strength of the firm effect in both the independent variable and the residual.

The results of the simulations are reported in Table 1. The first two entries in each cell are the average value of the slope coefficient and the standard deviation of the coefficient estimate. The standard deviation is the true standard error of the coefficient and ideally the estimated standard error will be close to this number. The average standard error estimated by OLS is the third entry in each cell and is the same as the true standard error in the first row of the table. When there is no firm effect in the residual (i.e. the residuals are independent across observations), the standard error estimated by OLS is correct (see Table 1, row 1). When there is no firm effect in the independent variable (i.e. the independent variable is independent across observations), the standard errors estimated by OLS are also correct on average, even if the residuals are correlated (see Table 1, column 1). This follows from the intuition in equation (7). The bias in the OLS standard errors is a product of the dependence in the independent variable (ρ_X) and the residual (ρ_ε). When either correlation is zero, OLS standard errors are unbiased.

When there is a firm effect in both the independent variable and the residual, then the OLS standard errors underestimate the true standard errors, and the magnitude of the underestimation can be large. For example, when fifty percent of the variability in both the residual and the independent variable is due to the fixed firm effect ($\rho_X = \rho_\varepsilon = 0.50$), the OLS estimated standard error is one half of the true standard error (0.557 = 0.0283/0.0508).[7] The standard errors estimated by OLS do not change as the firm effect increases across either the columns (i.e. in the independent variable) or across the rows (i.e. in the residual). The true standard error rises.

When I estimate the standard error of the coefficient using Rogers (clustered) standard errors, the estimates are very close to the true standard error. These estimates rise along with the true standard error as the fraction of variability arising from the firm effect increases. The Rogers robust standard errors correctly account for the dependence in the data common in a panel data set (Rogers, 1993, Williams, 2000).

An alternative way to examine the magnitude of the bias in the standard error estimates is to examine the empirical distribution of the simulated t-statistics. The t-statistics based on the OLS standard errors are too large in absolute value (see Figure 2-A). 15.3 percent of the OLS t-statistics are statistically significant at the 1 percent level (i.e. greater than 2.58). This is the intuition we saw in Tables 1. The Rogers standard errors are correct on average (see Table 1), and the empirical distribution of the t-statistics is also correct (see Figure 2-B). 0.9 percent of the Rogers t-statistics are significant at the one percent level. The reason the t-statistics give us the same intuition as the standard errors is because the standard errors are estimated very precisely. For example, the mean

[7] All of the regressions contained a constant whose true value is zero. The above intuition carries over to the intercept estimation. The estimated slope coefficient averages -0.0003 with a standard deviation of 0.0669, when $\rho_X = \rho_\varepsilon = 0.50$. The OLS standard errors are biased (0.0283) and the Rogers standard errors are correct on average (0.0663).

The simulated residuals are homoscedastic, so calculating standard errors which are robust to heteroscedasticity is not necessary in this case. When I estimated White standard errors in the simulation they have the same bias as the OLS standard errors. For example, the average White standard error was 0.0283 compared to the OLS estimate of 0.0283 and a true standard error of 0.0508 when $\rho_X = \rho_\varepsilon = 0.50$.

OLS standard error is 0.0282 with a standard deviation of 0.0007 and the mean Rogers standard error is 0.0508 with a standard deviation of 0.0027 (when $\rho_X = \rho_\varepsilon = 0.50$).

The bias in OLS standard errors is highly sensitive to the number of time periods (years) used in the estimation as well. As the number of years doubles, OLS assumes a doubling of the information. However if the independent variable and the residual are correlated within the cluster, the amount of information (independent variation) increases by less than a factor of two. The bias rises from about 30 percent when there are five years of data per firm to 73 percent when there are 50 years (when $\rho_X=\rho_\varepsilon=0.50$, see Figure 3). The robust standard errors are consistently close to the true standard errors independent of the number of time periods (see Figure 3).

Most of the simulations in the paper are based on linear regressions. To evaluate the performance of the standard error estimates in a non-linear setting, I simulated data according to equations 4 and 5. I took y as the latent variable and either censored the bottom 25% of the data (y<-1.5) or created a dummy variable (equal to one if y is positive, and zero otherwise). With this data I estimated a tobit and a probit model. The usual ("OLS") standard errors are too small and the Rogers standard errors are correct. The magnitude of the underestimate is the same as reported in Table 1 for the tobit model and slightly smaller in the probit model. These results are available from the author.

C) Fama-MacBeth Standard Errors: The Equations

An alternative way to estimate the regression coefficients and standard errors when the residuals are not independent is the Fama-MacBeth approach (Fama and MacBeth, 1973).[8] In this

[8] There several differences between OLS and Fama-MacBeth estimates (Jagannathan, and Wang, 1998). Fama-MacBeth traditionally weights each year of data equally even if there is a different number of observations per year. Thus in an unbalanced panel data set, the coefficient estimates can differ (Cohen, Gompers, and Vuolteenaho, 2002, Vuolteenaho, 2002). Fama-MacBeth also runs cross sectional regressions, and thus any variable which does not vary

approach, the researcher runs T cross sectional regressions. The average of the T estimates is the coefficient estimate.

$$\hat{\beta}_{FM} = \sum_{t=1}^{T} \frac{\hat{\beta}_t}{T}$$

$$= \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{i=t}^{N} X_{it} \, Y_{it}}{\sum_{i=t}^{N} X_{it}^2} \right) = \beta + \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{i=t}^{N} X_{it} \, \varepsilon_{it}}{\sum_{i=t}^{N} X_{it}^2} \right) \tag{8}$$

and the estimated variance of the Fama-MacBeth estimate is calculated as:

$$S^2(\hat{\beta}_{FM}) = \frac{1}{T} \sum_{t=1}^{T} \frac{(\hat{\beta}_t - \hat{\beta}_{FM})^2}{T - 1} \tag{9}$$

The variance formula, however, assumes that the yearly estimates of the coefficient (β_t) are independent of each other. This is only correct if $X_{it}\ \varepsilon_{it}$ is uncorrelated with $X_{is}\ \varepsilon_{is}$ for $t \neq s$. As discussed above, this is not true when there is a firm effect in the data (i.e. $\rho_X\ \rho_\varepsilon \neq 0$). Thus, Fama-MacBeth variance estimate is too small in the presence of a firm effect. In the presence of a firm effect, the true variance of the Fama-MacBeth estimate is:

$$\begin{aligned} \text{Var}(\hat{\beta}_{FM}) &= \frac{1}{T^2} \text{Var}\left(\sum_{t=1}^{T} \hat{\beta}_t\right) \\ &= \frac{\text{Var}(\hat{\beta}_t)}{T} + \frac{2 \sum_{t=1}^{T-1} \sum_{s=t+1}^{T} \text{Cov}(\hat{\beta}_t, \hat{\beta}_s)}{T^2} \\ &= \frac{\text{Var}(\hat{\beta}_t)}{T} + \frac{T\,(T-1)}{T^2} \text{Cov}(\hat{\beta}_t, \hat{\beta}_s) \end{aligned} \tag{10}$$

Given our specification of the data structure (equations 4 and 5), the covariance between the

across firms within a year (e.g. the stock market return) can not be estimated by the Fama-MacBeth method (Vuolteenaho, 2002, Cochrane, 2001). Since these have been dealt with elsewhere, I will not discuss them.

coefficient estimates of different years is independent of t-s (which justifies the simplification in the last line of equation 10) and can be calculated as follows if $t \neq s$:

$$\begin{aligned}
\operatorname{Cov}(\hat{\beta}_t, \hat{\beta}_s) &= \operatorname{plim}\left[\left(\sum_{i=1}^{N} X_{it}^2\right)^{-1}\left(\sum_{i=1}^{N} X_{it}\,\varepsilon_{it}\right)\left(\sum_{i=1}^{N} X_{is}\,\varepsilon_{is}\right)\left(\sum_{i=1}^{N} X_{is}^2\right)^{-1}\right] \\
&= (N\,\sigma_X^2)^{-2}\ \operatorname{plim}\left[\left(\sum_{i=1}^{N} X_{it}\,\varepsilon_{it}\right)\left(\sum_{i=1}^{N} X_{is}\,\varepsilon_{is}\right)\right] \\
&= (N\,\sigma_X^2)^{-2}\ \operatorname{plim}\left[\sum_{i=1}^{N} X_{it}\,X_{is}\,\varepsilon_{it}\,\varepsilon_{is}\right] \\
&= (N\,\sigma_X^2)^{-2}\ N\,\rho_X\,\sigma_X^2\,\rho_\varepsilon\,\sigma_\varepsilon^2 \\
&= \frac{\rho_X\,\rho_\varepsilon\,\sigma_\varepsilon}{N\,\sigma_X^2}
\end{aligned} \qquad \mathbf{(11)}$$

Combining equations (10) and (11) gives us an expression for the true variance of the Fama-MacBeth coefficient estimates.

$$\begin{aligned}
\operatorname{Var}(\hat{\beta}_{FM}) &= \frac{\operatorname{Var}(\hat{\beta}_t)}{T} + \frac{T\,(T-1)}{T^2}\operatorname{Cov}(\hat{\beta}_t, \hat{\beta}_s) \\
&= \frac{1}{T}\left(\frac{\sigma_\varepsilon^2}{N\,\sigma_X^2}\right) + \frac{T\,(T-1)}{T^2}\left(\frac{\rho_X\,\rho_\varepsilon\,\sigma_\varepsilon^2}{N\,\sigma_X^2}\right) \\
&= \frac{\sigma_\varepsilon^2}{NT\,\sigma_X^2}\left(1 + (T-1)\,\rho_X\,\rho_\varepsilon\right)
\end{aligned} \qquad \mathbf{(12)}$$

This is same as our expression for the variance of the OLS coefficient (see equation 7). Thus the Fama-MacBeth estimated standard error is too small in exactly the same cases as the OLS estimated standard error. In both cases, the magnitude of the underestimation is a function of the correlation of both the independent variable and the residual within a cluster and the number of time periods per firm.

D) Simulating Fama-MacBeth Standard Errors.

To document the bias of the Fama-MacBeth standard error estimates, I calculate the Fama-MacBeth estimate of the slope coefficient and the standard error in each of the 5,000 simulated data sets which were used in Table 1. The results are reported in Table 2. The Fama-MacBeth estimates are consistent and as efficient as OLS (the correlation between the two is consistently above 0.99). The standard deviation of the two coefficient estimates is also the same (compare the second entry in each cell of Table 1 and 2). Like the OLS standard error estimates, the Fama-MacBeth standard errors are biased downward (see Table 2).

The magnitude of the bias, however, is larger than implied by equation (12) and larger than the OLS bias. For example, when both ρ_X and ρ_ε are equal to 75 percent, the OLS standard error has a bias of 60% (0.595 = 1 - 0.0283/0.0698, see Table I) and the Fama-MacBeth standard error has a bias of 74 percent (0.738 = 1 - 0.0699/0.0183, see Table II). Moving down the diagonal of Table 2 from upper left to bottom right, the true standard error increases but the standard error estimated by Fama-MacBeth shrinks. As the firm effect becomes larger ($\rho_X \, \rho_\varepsilon$ increases), the bias in the OLS standard error grows, but the bias in the Fama-MacBeth standard error grows even faster.[9] The incremental bias of the Fama-MacBeth standard errors is due to the way in which the estimated variance is calculated. To see this we need to expand the expression of the estimated variance (equation 9).

[9] The distribution of empirical t-statistics is even wider for the Fama-MacBeth than for OLS (see Figures 2-A and 2-C). 24.5 percent of the Fama-MacBeth t-statistics are statistically significant at the 1 percent level compared to 15.3 percent of the OLS t-statistics (when $\rho_X = \rho_\varepsilon = 0.50$).

$$
\begin{aligned}
\mathrm{Var}[\,\beta_{FM}\,] &= \frac{1}{T(T-1)} \sum_{t=1}^{T} \left[\frac{\sum_{i=1}^{N} X_{it}\ \varepsilon_{it}}{\sum_{i=1}^{N} X_{it}^2} - \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{i=1}^{N} X_{it}\ \varepsilon_{it}}{\sum_{i=1}^{N} X_{it}^2} \right) \right]^2 \\
&= \frac{1}{T(T-1)} \sum_{t=1}^{T} \left[\frac{\sum_{i=1}^{N} (\mu_i + \nu_{it})(\gamma_i + \eta_{it})}{\sum_{i=t}^{N} (\mu_i + \nu_{it})^2} - \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{i=1}^{N} (\mu_i + \nu_{it})(\gamma_i + \eta_{it})}{\sum_{i=1}^{N} (\mu_i + \nu_{it})^2} \right) \right]^2
\end{aligned}
\qquad \textbf{(13)}
$$

The true variance of the Fama-MacBeth coefficients is a measure of how far each yearly coefficient estimate deviates from the true coefficient (one in our simulations). The estimated variance, however, measures how far each yearly estimate deviates from the sample average. Since the firm effect influences both the yearly coefficient estimate and the sample average of the yearly coefficient estimates, it does not appear in the estimated variance. Thus increases in the firm effect (increases in $\rho_X\rho_\varepsilon$) actually reduce the estimated Fama-MacBeth standard error at the same time it increases the true standard error of the estimated coefficients. To make this concrete, take the extreme example where $\rho_X\rho_\varepsilon$ is equal to one. OLS underestimates the standard errors by a factor of $\sqrt{T}$ (the standard error estimated by OLS is $(\sigma_\varepsilon/NT\sigma_X)^{1/2}$ while the true standard error is $(\sigma_\varepsilon/N\sigma_X)^{1/2}$. The estimated Fama-MacBeth standard error is zero. This additional source of bias shrinks as the number of years increases since the estimated slope coefficient will converge to the true coefficient (see Figure 3).

The firm effect may be less important in regressions where the dependent variable is returns (and excess returns are serially uncorrelated) than in corporate finance applications where unobserved firm effects can be very important (see Section VI). The biases which I have highlighted are less important in those applications. This isn't surprising since the Fama-MacBeth technique was developed to account for correlation between observations on different firms in the same year, not to account for correlation between observations on the same firm in different years. In fact, Fama and MacBeth (1973) examine the serial correlation of the residuals in their results and find that it is close to zero. Its application in the literature, however, has not always been consistent with its roots. Given the Fama-MacBeth approach was designed to deal with time effects in a panel data set, not firm effects, I turn to this data structure in the next section.

E) Newey-West Standard Errors.

An alternative approach for addressing the correlation of errors across observation is the Newey-West procedure (Newey and West, 1987). This procedure is traditionally used to account for serial correlation of unknown form in the residuals of a single time series. It can be modified for use in a panel data set by estimating only correlations between lagged residuals in the same cluster (see Bertrand, Duflo, and Mullainathan, 2004, Doidge, 2004, MacKay, 2003, Brockman and Chung, 2001). The problem of choosing a lag length is simplified in a panel data set, since the maximum lag length is one less than the maximum number of years per firm.[10] To examine the relative performance of the Newey-West, I simulated 5,000 data sets with 5,000 observations each. Each data set includes 500 firms and ten years of data per firm. The fixed firm effect was assumed to account for twenty-five percent of the variability of both the independent variable and the residual.

The standard error estimated by the Newey-West is an increasing function of the lag length in this simulation. When the lag length is set to zero, the estimated standard error is numerically

[10] In the standard application of Newey-West, a lag length of M implies that the correlation between ε_t and ε_{t-k} are included for k running from -M to M. When Newey-West has been applied to panel data sets, correlations between lagged and leaded values are only included when they are drawn from the same cluster. Thus a cluster which contains T years of data per firm uses a maximum lag length of T-1 and would include t-1 lags and T-t leads for the t^{th} observation where t runs from 1 to T.

identical to the White standard error, which is only robust to heteroscedasticity. This is the same as the OLS standard error in my simulation, since the residuals are homoscedastic. Not surprisingly, this estimate significantly underestimates the true standard error (see Figure 4). As the lag length is increased from 0 to 9, the standard error estimated by the Newey-West rises from the OLS/White estimate of 0.0283 to 0.0328 when the lag length is 9 (see Figure 4). In the presence of a fixed firm effect, an observation of a given firm is correlated with all other observations for the same firm no matter how far apart in time the observations are spaced. Thus having a lag length of less than the maximum (T-1), will cause the Newey-West standard errors to underestimate the true standard error when the firm effect is fixed (we return to temporary firm effects in Section V). However, even with the maximum lag length of 9, the Newey-West estimates have a small bias – underestimating the true standard error by 8% [0.084 = 1-0.0328/0.0358].

As the simulation demonstrates, the Newey-West approach to estimating standard errors, as applied to panel data, does not yield the same estimates as the Rogers standard errors. The difference between the two estimates is due to the weighting function used by Newey West. When estimating the standard errors, Newey-West multiplies the covariance term of lag j (e.g. $\varepsilon_t \, \varepsilon_{t-j}$) by the weight [1-j/(M+1)], where M is the specified maximum lag. If I set the maximum lag equal to T-1, then the central matrix in the variance equation of the Newey-West standard error is:

$$\begin{aligned}
\sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}\ \varepsilon_{it}\right)^2 &= \sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}^2\,\varepsilon_{it}^2 + 2\sum_{t=1}^{T-1}\sum_{s=t+1}^{T} w(t-s)\,X_{it}\,X_{is}\,\varepsilon_{it}\,\varepsilon_{is}\right)\\
&= \sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}^2\,\varepsilon_{it}^2 + 2\sum_{t=1}^{T-1}\sum_{j=1}^{T-t} w(j)\,X_{it}\,X_{it-j}\,\varepsilon_{it}\,\varepsilon_{it-j}\right) \qquad \textbf{(14)}\\
&= \sum_{i=1}^{N}\left(\sum_{t=1}^{T} X_{it}^2\,\varepsilon_{it}^2 + 2\sum_{t=1}^{T-1}\sum_{j=1}^{T-t}\left(1-\frac{j}{T}\right) X_{it}\,X_{it-j}\,\varepsilon_{it}\,\varepsilon_{it-j}\right)
\end{aligned}$$

This is identical to the term in the Rogers standard error formula (see footnote 5) except for the weighting function [w(j)]. The Rogers standard errors use a weighting function of one for all co-variances. The Newey-West procedure was originally designed for a single time-series and the weighting function was necessary to make the estimate of this matrix positive semi-definite. For fixed j the weight w(j) approaches 1 as the maximum lag length (M) grows. Newey and West show that if M is allowed to grow at the right rate with the sample size (T), then their estimate is consistent. However, in the panel data setting, the number of time periods is usually small. The consistency of the Rogers standard error is based on the number of clusters (N) being large, opposed to the number of time periods (T). Thus the Newey-West weighting function is unnecessary and leads to standard error estimates which have a slightly bias in a panel data setting.[11]

III) Estimating Standard Errors in the Presence of a Time Effect.

To demonstrate how the techniques work in the presence of a time effect I will generate data sets which contain only a time effect (observations on different firms with in the same year are correlated). This is the data structure for which the Fama-MacBeth approach was designed (see Fama-MacBeth, 1973). If I assume that the panel data structure contains only a time effect, the equations I derived above are essentially unchanged. The expressions for the standard errors in the presence of only a time effect are correct once I exchange N and T.

A) Rogers Standard Error Estimates.

[11] Although the bootstrap method of estimating standard errors was rarely used in the articles which I surveyed, it is an alternative way to estimate the standard errors in a panel data set (see for example Kayhan and Titman, 2004 and Efron and Tibshirani, 1986). To test its relative performance, I drew 100 samples with replacement and re-estimated the regression for each simulated data set. When I drew observations independently (e.g. I drew 5,000 firm-year), the estimated standard errors are the same as the OLS standard errors reported in Table I (e.g. 0.0282 for the bootstrap versus 0.0283 for OLS when $\rho_X = \rho_\varepsilon = 0.50$). When I drew observations as a cluster (e.g. I drew 500 firms with replacement and took all 10 years for any firm which was drawn), the estimated standard errors are the same as the Rogers standard errors (e.g. 0.0505 for bootstrap versus 0.0508 for Rogers). The results were essentially the same when I drew 1,000 samples for each simulated data set.

Simulating the data with only a time effect means the dependent variable will still be specified by equation (1), but now the error term and independent variable are specified as:

$$\begin{aligned} \varepsilon_{it} &= \delta_t + \eta_{it} \\ X_{it} &= \zeta_t + \nu_{it} \end{aligned} \tag{15}$$

As before, I simulated 5,000 data sets of 5,000 observations each. I allowed the fraction of variability in both the residual and the independent variable which is due to the time affect to range from zero to seventy-five percent in twenty-five percent increments. The OLS coefficient, the true standard error, as well as the OLS and robust standard error estimates are reported in Table 3. There are several interesting findings to note. First, as with the firm effect results, the OLS standard errors are correct when there is no time effect in either the independent variable ($\sigma(\zeta)=0$) or the residual ($\sigma(\delta)=0$). As the time effect in the independent variable and the residual rise, so does the magnitude by which the OLS standard errors underestimate the true standard errors. When half of the variability in both comes from the time effect, the OLS standard errors underestimate the true standard errors by 91 percent [0.909 = 1 - 0.0282/0.3105, see Table 3].

The robust standard errors are much more accurate, but unlike our results with the firm effects, they also underestimate the true standard error. The magnitude of the underestimate is small, ranging from 13 percent [1-0.1297/0.1490] when the time effect accounts for 25 percent of the variability to 19 percent [1-0.3986/0.4927] when the time effect accounts for 75 percent of the variability. The problem arises due to the limited number of clusters (e.g. years). When I estimated the standard errors in the presence of the firm effects, I had 500 firms (clusters). When I estimated the standard errors in the presence of a time effect, I have only 10 years (clusters). Since the robust standard errors method places no restriction on the correlation structure of the residuals within a cluster, its consistency depends upon having a sufficient number of clusters to estimate the standard errors. Based on these results, 10 clusters is too small and 500 is sufficient (see Kezdi, 2004, and Bertrand, Duflo, and Mullainathan, 2004, for similar results).

To explore this issue further, I simulated data sets of 5,000 observations with the number of years (or clusters) ranging from 10 to 100. In all of the simulations, 25 percent of the variability in both the independent variable and the residual is due to the time effect [i.e. $\sigma^2(\delta)/\sigma^2(\varepsilon) = \sigma^2(\zeta)/\sigma^2(X) = 0.25$]. The bias in the robust standard error estimates declines with the number of clusters, dropping from 13 percent when there are 10 years (or clusters) to 4 percent when there are 40 years to under 1 percent when there are 100 years (see Figure 5). Thus, the bias in the robust standard error estimates is a product of the small number of clusters. However, since panel data sets of 10 or 20 years are not uncommon in finance, this may be a concern in practice.

B) Fama-MacBeth Standard Errors.

When there is only a time effect, the correlation of the estimated slope coefficients across years is zero and the standard errors estimated by Fama-MacBeth are correct (see equation 9 and 12). This is exactly what we find in the simulation (see Table 4). The estimated standard errors are extremely close to the true standard errors and the confidence intervals are the correct size. In addition to producing unbiased standard error estimates, Fama-MacBeth also produces more efficient estimates than OLS. For example, when 25 percent of the variability of both the independent variable and the residual is due to the time effect, the standard deviation of the Fama-MacBeth coefficient estimate is 81 percent [1-0.0284/0.1490] smaller than the standard deviation of the OLS estimate (compare Table 3 and 4). The improvement in efficiency arises from the way in which Fama-MacBeth accounts for the time effect. By running cross sectional regressions for each year the intercept absorbs, and is an estimate of, the time effect. Since the variability due to the time effect is no longer in the residual, the residual variability is significantly smaller. The lower residual variance leads to less variable coefficient estimates and greater efficiency. I will revisit this issue in the next section when I consider the presence of both a firm and a time effect.

IV) Estimating Standard Errors in the Presence of a Fixed Firm Effect and Time Effect.

According to the simulation results thus far, the best method for estimating the coefficient and standard errors in a panel data set depends upon the source of the dependence in the data. If the panel data only contains a firm effect, the Rogers standard errors (clustered by firm) are superior as they produce unbiased standard errors. If the data has only a time effect, the Fama-MacBeth estimates perform better than Rogers standard errors (clustered by time) when there are few years (clusters) and equally well when the number of years (clusters) is large. The Fama-MacBeth estimates are more efficient than the OLS coefficients, although as we will see below this advantage disappears if time dummies are included.

Although the above results are instructive, they are unlikely to be completely descriptive of actual data confronted by empirical financial researchers. Panel data sets may include both a firm effect and a time effect. Thus to provide guidance on which method to use I need to assess their relative performance when both effects are present. In this section, I will simulate a data set where both the independent variable and the residual have both a firm and a time effect.

A conceptual problem with using these techniques (Rogers or Fama-MacBeth standard errors) is neither is designed to deal with correlation in two dimensions (e.g. across firms and across time).[12] The robust standard error approach allows us to be agnostic about the form of the correlation within a cluster. However, the cost of this is the residuals must be uncorrelated across clusters. Thus if we cluster by firm, we must assume there is no correlation between residuals of different firms in the same year. In practice, empirical researchers account for one dimension of the cross observation correlation by including dummy variables and account for the other dimension by clustering on that dimension. Since most panel data sets have more firms than years, the most common approach is to include dummy variables for each year (to absorb the time effect) and then cluster by firm (Anderson and Reeb, 2004, Gross and Souleles, 2004, Petersen and Faulkender, 2004, Sapienza, 2004, and Lamont and Polk, 2001). I will use this approach in my simulations.

A) Rogers Standard Error Estimates.

To test the relative performance of the two methods, 5,000 data sets were simulated with both a firm and a time effect. Across the simulations, the fixed firm effect accounts for either 25 or 50 percent of the variability. The fraction of the variability due to the time effect is also assumed to be 25 or 50 percent of the total variability. This gives us three possible scenarios for the independent variable [(25,25),(25,50), and (50,25)]. The same three scenarios were used for simulating the residual, for a total of nine simulations (see Table 5).

The results in the presence of both a firm and time effect (Table 5) are qualitatively similar to what we found in the presence of only a fixed firm effect (Table 1). The OLS standard errors underestimate the true standard errors whereas the Rogers (clustered by firm) standard errors are

[12] It is possible to estimate robust standard errors accounting for clustering in multiple dimensions, but only if there are a sufficient number of observations within each cluster. For example, if a researcher has observations on firms in industries across multiple years, she could cluster by industry and year (i.e. each cluster would be a specific year and industry, see Lipson and Mortal, 2004). In this case, since there are multiple firms in a given industry in each year, clustering would be possible. If clustering was done by firm and year, since there is only one observation within each cluster, this is numerically identical to White standard errors.

consistently accurate independent of how I specify the firm and time effects. As we saw above, the bias in the OLS standard errors increases as the firm effect becomes larger.[13]

B) Fama-MacBeth Estimates

The statistical properties of the OLS and Fama-MacBeth coefficient estimates are quite similar. The means and the standard deviations of the estimates are almost identical (see Table 5 and Table 6), and the correlation between the two estimates is never less than 0.999 in any of the simulations. Once I include a set of time dummies in the OLS regression, the difference in efficiency I found in Tables 3 and 4 disappears. The OLS estimates are now as efficient as the Fama-MacBeth, even in the presence of a time effect. The standard errors estimated by Fama-MacBeth, however, are once again too small, just as I found in the absence of a firm effect (Table 2). When 25 percent of the variability is from the firm effect and 25 percent comes from a time effect, the Fama-MacBeth standard errors underestimate the true standard errors by 37 percent [1-0.0258/0.0407].

Most of the intuition from the earlier tables carries over. In the presence of a fixed firm effect both OLS and Fama-MacBeth standard error estimates are biased down significantly. Rogers standard errors which account for clustering by firm produce estimates which are correct on average. The presence of a fixed time effect, if it is controlled for with dummy variables, does not alter these results, except for accentuating the magnitude of the firm effect and thus making the bias in the OLS and Fama-MacBeth standard errors larger.

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[13] The magnitude of the time effect does affect the magnitude of the bias in the OLS estimates, although the intuition is subtle. To understand the intuition, it is useful to examine several examples. In Table 1, when the firm effect is 25 percent of the variability of both the independent variable and the residual, OLS underestimates the standard error by 20 percent [1-0.0283/0.0353]. In Table 5, there are two scenarios where the fixed firm effect is 25 percent for both the independent variable and the residual. When the magnitude of the time effect rises to 25 percent, the bias in OLS rises to 31 percent [1-0.0283/0.0407], and when the magnitude of the time effect rises to 50 percent, the bias in the OLS standard error is 45 percent [1-0.0283/0.0515]. By absorbing the variability due to the time effect from the residual and the independent variable, the time dummies raise the fraction of the remaining variability which is due to the firm effect (i.e ρ_X or ρ_ε rise). This increases the bias in the OLS standard errors.

V) Estimating Standard Errors in the Presence of a Temporary Firm Effect

The analysis thus far has assumed that the firm effect is fixed. Although this is common in the literature, it may not always be accurate. The dependence between residuals may decay as the time between them increases (i.e. $\rho(\varepsilon_t , \varepsilon_{t-k})$ may decline with k). In a panel with a short time series, distinguishing between a permanent and a temporary firm effect may be impossible. However, as the number of years in the panel increases it may be feasible to empirically identify the permanence of the firm effect. In addition, if the performance of the different standard error estimators depends upon the permanence of the firm effect, researchers need to know this.

A) Temporary Firm Effects: Specifying the Data Structure.

To explore the performance of the different standard error estimates in a more general context, I simulated a data structure which includes both a permanent component (a fixed firm effect) and a temporary component (non-fixed firm effect) which I assume is a first order auto regressive process. This allows the firm effect to die away at a rate between a first order auto-regressive decay and zero. To construct the data, I assumed that non-firm effect portion of the residual ($\eta_{i\,t}$ from equation 4) is specified as

$$\begin{aligned} \eta_{it} &= \varsigma_{it} && \text{if } t = 1 \\ &= \varphi\, \eta_{it-1} + \sqrt{1-\varphi^2}\, \varsigma_{it} && \text{if } t > 1 \end{aligned} \qquad \textbf{(16)}$$

Thus φ is the first order auto correlation between η_{it} and η_{it-1}, and the correlation between $\eta_{i\,t}$ and $\eta_{i,t-k}$ is φ^k.[14] Combining this term with the fixed firm effect (γ_i in equation 4), means the serial correlation

[14] I multiply the ς term by $\sqrt{1 - \varphi^2}$ to make the residuals homoscedastic. From equation (16),

$$\begin{aligned} \mathrm{Var}(\eta_{it}) &= \sigma_\varsigma^2 && \text{if } t = 1 \\ &= \varphi^2\, \sigma_\varsigma^2 + (1-\varphi^2)\, \sigma_\varsigma^2 = \sigma_\varsigma^2 && \text{if } t > 1 \end{aligned}$$

of the residuals dies off over time, but more slowly than implied by a first order auto-regressive and asymptotes to ρ_ε (from equation 6). By choosing the relative magnitude of the fixed firm effect (ρ_ε) and the first order auto correlation (φ), I can alter the pattern of auto correlations in the residual. The correlation of lag length k is:

$$
\begin{aligned}
Corr(\varepsilon_{i,t}, \varepsilon_{i,t-k}) &= \frac{Cov(\gamma_i + \eta_{i,t}, \gamma_i + \eta_{i,t-k})}{\sqrt{Var(\gamma_i + \eta_{i,t})\, Var(\gamma_i + \eta_{i,t-k})}} \\
&= \frac{\sigma_\gamma^2 + \varphi^k \sigma_\eta^2}{\sigma_\gamma^2 + \sigma_\eta^2} \\
&= \rho_\varepsilon + (1 - \rho_\varepsilon)\,\varphi^k
\end{aligned}
\qquad \textbf{(17)}
$$

An analogous data structure is specified for the independent variable. The correlation for lags one through nine for the four data specifications I will examine are graphed in Figure 6. They range from a fixed firm effect (ρ=0.25 and φ=0.00) to a standard AR1 process (ρ=0.00 and φ=0.75). I have assumed the same process for both the independent variable and the residual, since as we know from Section II, if there is no within cluster dependence in the independent variables, OLS standard errors are correct.

B) Fixed Effects – Firm Dummies.

A significant minority of the papers in the survey, used fixed effects to control for dependence within a cluster. Using the simulations, I can compare the relative performance of OLS and Rogers standard errors both with and without firm dummies. The results are reported in Table 7, Panel A. The fixed effect estimates are more efficient in this case (e.g. 0.0299 versus 0.0355),

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where the last step is by recursion (if it is true for t=m, it is true for t=m+1). Assuming homoscedastic residuals is not necessary since the Rogers standard errors are robust to heteroscedasticity. However, assuming homoscedasticity makes the interpretation of the results simpler. If I assume the residuals are homoscedastic, then any difference in the standard errors I find is due to the dependence of observations within a cluster opposed to the presence of heteroscedasticity.

although this is not always true. The relative efficiency of the fixed effect estimates depends upon two offsetting effects. Including the firm dummies uses up N–1 additional degrees of freedom and this raises the standard deviation of the estimate. However, the firm dummies also eliminate the within cluster dependence of the residuals which reduces the standard deviation of the estimate. In this example, the second effect dominates and thus the fixed effect estimates are more efficient.

Once we include the firm effects, the OLS standard error are now correct and the Rogers standard errors are not necessary (see Table 7 - Panel A, column I).[15] The Rogers standard errors are correct when we do not include the fixed effects and are slightly too large (5%) when we include the fixed effects (see Kezdi, 2004, for similar results). This conclusion, however, is sensitive to the firm effect being fixed. If the firm effect decays over time, the firm dummies no longer completely capture the within cluster dependence and OLS standard errors are still biased (see Table 7 - Panel A, columns II-IV). In these simulations, the firm effect decays over time (in column II, 92 percent of the firm effect dissipates after 9 years). Once the firm effect is temporary, the OLS standard errors again underestimate the true standard errors even when firm dummies are included in the regression (Wooldridge, 2004, Baker, Stein, and Wurgler, 2003). The magnitude of the underestimation depends upon the magnitude of the temporary component of the firm effect (i.e. φ). The bias rises from about 17% when φ is 50 percent (column IV) to about 33 percent when φ is 75% (columns II and III).

C) Adjusted Fama-MacBeth Standard Errors.

[15] I assumed the model is correctly specified [i.e. Corr($X_{i\,t}$, $\varepsilon_{i\,t}$) = 0]. Thus the only purpose of including fixed effects, in this case, is to correct the standard errors. In real applications, the model may not be correctly specified [i.e. Corr($X_{i\,t}$, $\varepsilon_{i\,t}$) ≠ 0], and so including fixed effects may be necessary as part of a model specification test (see Hausman, 1978). Instead of including firm dummies, we could have first differenced the data within firm. It would still be necessary to use Rogers opposed to OLS standard error estimates, since the residuals would still be correlated

As noted in Section II, the presence of a firm effect cause the Fama-MacBeth yearly coefficient estimates to be correlated and this causes the Fama-MacBeth standard error to be biased downward. Several authors have acknowledged the bias and have suggested adjusting the standard errors for the estimated first order auto-correlation of the estimated slope coefficients (Pontiff, 1996, Graham, Lemmon, and Schallheim, 1998; Christopherson, Ferson, and Glassman, 1998; Chen, Hong, and Stein, 2001; Cochrane, 2001; Lakonishok, and Lee, 2001; Fama and French, 2002; Bakshi, Kapadia, and Madan, 2003; Chakravarty, Gulen, and Mayhew, 2004). The proposed adjustment is to estimate the correlation between the yearly coefficient estimates (i.e. Corr[β_t, β_{t-1}] = θ), and then multiply the estimated variance by $(1+\theta)/(1-\theta)$ to account for serial correlation of the βs (see Chakravarty, Gulen, Mayhew, 2004 and especially Fama and French, 2002, footnote 1). This makes intuitive sense since the presence of a firm effect will cause the yearly coefficient estimates to be serially correlated.

To test the merits of this idea, I simulated data sets where the fixed firm effect accounts for 25 percent of the variance. For each simulated data set, ten slope coefficients are estimated, and the auto-correlation of the slope coefficients is calculated. I then calculate the original and adjusted Fama-MacBeth standard errors, assuming both an infinite and a finite lag of T-1 periods (see Lakonishok and Lee, 2001).[16] The autocorrelation is estimated imprecisely as predicted by Fama and

[16] Thus, instead of multiplying the variance by the infinite period adjustment [(1+θ)/(1-θ)], I multiplied it by the 10 period adjustment

$$\text{Variance correction} = \left(1 + 2\sum_{k=1}^{10-1} (10 - k)\ \theta^k\right)$$

A third alternative is to estimate a k order auto-regressive model on the yearly βs, and then use the intercept and its standard error as an estimate of β and its standard error (see Pontiff, 1996). This bias in this method is similar to those reported in Table 7 (results available from the author).

French (2002). The 90th percentile confidence interval ranges from -0.60 to 0.41, but the mean is -0.1134 (see Table 7 - Panel B). Since the average first-order auto-correlation is negative, the adjusted Fama-MacBeth standard errors are even smaller and more biased than the unadjusted standard errors.

We saw the intuition behind the biased auto-correlations above. The problem is the correlation being estimated (the within sample auto-correlation of betas) is not the same as the one which is causing the bias in the standard errors (the population auto-correlation of betas). The co-variance which biases the standard errors and which I can estimate across the 5,000 simulations is:

$$\mathrm{Cov}(\beta_t, \beta_{t-1}) = E[(\beta_t - \beta_{True})(\beta_{t-1} - \beta_{True})] \qquad \textbf{(18)}$$

To see how the presence of a fixed firm effect influences this covariance, consider the case where the realization for firm i is a positive value of $\mu_i\gamma_i$ (i.e. the realized firm effect in the independent variable and the residual). This positive realization will result in an above average estimate of the slope coefficient in year t, and because the firm effect is fixed it will also result in an above average estimate of the slope coefficient in year t-1 (see equation 8). The realized value of the firm effect (μ_i and γ_i) in a given simulation does not change the average β across samples. The average β across samples is the true β or one in the simulations. Thus when I estimate the true correlation between β_t and β_{t-1}, the firm effect causes this correlation to be positive and the adjusted and unadjusted Fama-MacBeth standard errors to be biased downward.[17]

Researchers are given only one data set. Thus they must calculate the serial correlation of

[17] In the simulation the correlation between β_t and β_s ranged from 0.0430 to 0.0916 and did not decline as the difference between t and s increased (the firm effect is fixed). The theoretical value of the correlation between β_t and β_s should be 0.0625 (according to equation 11) and would imply a true standard error of the Fama-MacBeth estimate of 0.0354 (according to equation 12). These match the numbers I report in Table II.

the βs within the sample they are given. This co-variance is calculated as:

$$\mathrm{Cov}(\beta_t, \beta_{t-1}) = E[(\beta_t - \overline{\beta}_{\text{Within sample}})(\beta_{t-1} - \overline{\beta}_{\text{Within sample}})] \tag{19}$$

The within sample serial correlation measures the tendency of β_t to be above its within sample mean when β_{t-1} is above its within sample mean. To see how the presence of a fixed firm effect affects this covariance, consider the same case as above. A positive realization of $\mu_i\gamma_i$ will raise the estimate of β_1 through β_T, as well as the average of the βs (the Fama-MacBeth coefficient estimate) by the same amount. Thus a fixed firm effect will not influence the deviation of any β_t from the average β. Since this deviation is the source of the estimated within sample serial correlation, the serial correlation calculated in sample is asymptotically zero and adjusting the standard errors based on this estimated serial correlation will still lead to biased standard error estimates.[18]

The adjusted Fama-MacBeth standard errors do better when there is an auto-regressive component in the residuals (i.e. $\varphi > 0$). In the three remaining simulations in Table 7 – Panel B, the estimated within sample auto correlation is positive in all cases, but the adjusted Fama-MacBeth standard errors are still biased downward. Adjusting the standard error estimates moves them closer to the truth when the firm effect is not fixed (ρ=0). The standard errors based on the infinite period adjustment underestimate the true standard error by 23 percent (1-0.0374/0.0484, see Table 7 - Panel B, column II). As the magnitude of the firm effect increases (compare columns II to III and IV), the bias in the estimated standard errors increases. Thus the Fama-MacBeth standard errors adjusted for serial correlation do better than the unadjusted standard errors when the firm effect decays over time,

[18] The average within sample serial correlation I estimate is actually less than zero, but this is due to a small sample bias. With only ten years of data per firm, I have only nine observations to estimate the serial correlation. To verify that this is correct, I re-ran the simulation using 20 years of data per firm and the average estimated serial correlation moved closer to zero, rising from -0.1134 to -0.0556.

but they still significantly underestimate the true standard errors.

VI) Empirical Applications.

The analysis thus far has been on simulated data. In these examples, I had the advantage of knowing the data structure, which made choosing the method for estimating standard errors much easier. In real world applications, we may have priors about the data's structure (are firm effects or time effects more important and are they permanent or temporary), but we do not know the data structure for certain. Thus in this section, I will apply the different techniques for estimating standard errors to two real data sets. This way I can demonstrate how the different methods for estimating standard errors compare and also show what we can learn from the comparison.

For both data sets, I will first estimate the regression using OLS, and report White standard errors as well as Rogers standard errors clustered by firm and year (Tables 8 and 9, columns I-III). By using White standard errors as my baseline, difference across columns are attributable only to within cluster correlations, not to heteroscedasticity. If the Rogers standard errors clustered by firm are dramatically different than the White standard errors, then we know there is a significant firm effect in the data [e.g. Corr($X_{i\ t}\,\varepsilon_{i\ t}$, $X_{i\ t\text{-}k}\,\varepsilon_{i\ t\text{-}k}$) $\neq 0$]. I then estimate the slope coefficients and the standard errors using Fama-MacBeth (Tables 8 and 9, columns IV-V). Finally, I re-estimate OLS regression including firm dummies and report the slope coefficients and standard errors clustered by firm and time (Table 8 and 9, columns VI-VIII). Each of the OLS regressions include time dummies. This makes the efficiency of the OLS and Fama-MacBeth coefficients similar.[19]

[19] The reported R^2s do not include the explanatory power attributable to the time dummies. This is done to make the R^2 comparable between the OLS and the Fama-MacBeth results. Although the Fama-MacBeth procedure estimates a separate intercept for each year, the constant is calculated as the average of the yearly intercepts. Thus the Fama-MacBeth R^2 does not include the explanatory power of time dummies. Procedurally, I subtracted the yearly means off of each variable before running the OLS regressions.

A) Asset Pricing Application.

For the asset pricing example, I used the equity return regressions from Daniel and Titman (2004, "Market Reactions to Tangible and Intangible Information"). They regress monthly equity returns on annual values of lagged book to market ratios, historic changes in book and market values, and a measure of the firm's equity issuance. The data is briefly described in the appendix and in detail in their paper. Each observation of the dependent variable is a monthly equity return. However, the independent variables are annual values (based on the prior year). Thus for the twelve observations in a year, the dependent variable (equity returns) changes each month, but the independent variable (e.g. past book value) does not, and is therefore highly persistent.

The Rogers and White standard errors are essentially the same when I cluster by firm (ranging from three percent larger to one percent smaller). This occurs because the auto-correlation in the residuals is effectively zero (see Figure 7). The auto-correlation in the independent variable is large and persistent, starting at 0.98 the first month and declining to 0.49 to 0.75 by the 24th month depending upon the independent variable. However, since the adjustment in the standard error is a function of the monthly auto-correlation in the Xs (a large number) times the auto-correlation in the residuals (zero), the Rogers standard errors clustered by firm are no different than the White standard errors.

The story is very different when I clustered by time (months). The standard errors clustered by month are two to four times larger than the White standard errors. For example, the t-statistic on the lagged book to market ratio is 7.2 if we use the White standard error and 1.9 if we cluster by month. This means there is a significant time effect in the data (see Figure 8). Remember, however, that the regression already contains time dummies. So any fixed time effect (i.e. one which raises the monthly return for every firm in a given month by the same amount) has already been removed from the data and will thus not affect the standard errors. Thus, the remaining correlation in the time dimension must vary across observations (i.e. Corr[$\varepsilon_{it}\,\varepsilon_{jt}$] varies across i and j).

Understanding a temporary firm effect is straightforward. A firm effect dies off over time (is temporary) if the 1980 residual for firm A is more highly correlated to the 1981 residual for firm A than to the 1990 residual. This is how I simulated the data in Section V. Understanding a non-constant time effect is more difficult. For the time effect to be non-constant, it must be that a shock in 1980 has a large effect on firm A and B, but has a significantly smaller affect on firm Z. If the time effect influenced each firm in a given month by the same amount, the time dummies would absorb the effect and clustering by time would not change the reported standard errors. The fact that clustering by time does change the standard errors, means there must be a non-constant time effect.

If we know the data, we can use our economic intuition to determine how the data should be organized and predict the source of the dependence within a cluster. For example, since this data set contains monthly equity returns we might consider how a shock to returns would effect firms differently. If the economy booms in a given month, firms in the durable goods industry may rise more than firms in the non-durable goods industry. This can create a situation where the residuals of firms in the same industry are correlated (within the month) with each other but less correlated with firms in another industry. When I sort the data by month, four-digit industry and then firm, I see evidence of this in the auto-correlation for the residuals and the independent variables within each month. The results are graphed in Figure 8. The auto-correlations of the residual is much larger than when I sort by firm then month (compare Figure 7 and 8) and they die away as we consider firms in more distant industries.[20]

When calculating the Rogers standard errors clustered by time, we don't need to make an assumption about how to sort the data. However, if researchers are going to understand what the standard errors are telling them about the structure of the data, they need to consider the source of the dependence in the residuals. By examining how standard errors change when we cluster by firm or time (i.e. compare columns I to II and I to III), we can determine the nature of the dependence which remains in the residuals and this can guide us on how to improve our models.

According to the results in Sections II and III, the Fama-MacBeth standard errors perform better in the presence of a time effect than a firm effect, and so given the above results should do well in this data set. The Fama-MacBeth coefficients and standard errors are reported in column IV. These results are a replica of those reported by Daniel and Titman (see Table 3, row 8 in their paper). The coefficient estimates are similar to the OLS coefficients, and the standard errors are much larger than the White standard errors (2.0 to 3.4 times) as we would expect in the presence of a time effect. The Fama-MacBeth standard errors are close to the Rogers standard errors when we cluster by time, as both methods are designed to account for dependence in the time dimension. The Fama-MacBeth standard errors are consistently smaller than the Rogers standard errors, but the magnitude of the difference is not large (twelve to eighteen percent, compare columns III and IV of Table 8).

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[20] A non-constant time effect can be generated by a random coefficient model (Greene, 2004). For example, if the firm's return depends upon the firm's β times the market return, but only the market return or time dummies are included in the regression, then the residual will contain the term $\{ [\beta_i - \text{Average}(\beta_i)] \text{ Market return}_t \}$. Firms which have similar βs will have correlated residuals within a month, and firms which have very different βs will have residuals whose correlation is small. This is a non-constant time effect. This logic suggests that I should instead sort by month, β, and then firm. When I sort this way, the auto-correlations are smaller and die away more slowly (declining from 0.030 at a lag of one to 0.028 at a lag of 24) than when I sorted by month, four-digit industry and firm (declining from 0.096 at a lag of one to 0.042 at a lag of 24).

Cross-sectional, time-series regressions on panel data sets treat each observation equally. In the Fama-MacBeth procedure, the monthly coefficient estimates are averaged using equal weights for each month, but not each observation. Thus in an unbalanced panel, Fama-MacBeth effectively weights each observation proportional to $1/N_t$ where N_t is the number of firms in month t. Since the number of firms in this sample grows from about 1,000 per month at the beginning to almost 2,300 near the end of the sample, Fama-MacBeth will effectively under weight the later observations. To correct this, I took a weighted average of the monthly coefficient estimates where the weights were proportional to N_t. When I compare the weighted and un-weighted coefficient estimates and standard errors, they are very close (compare columns IV and V of Table 8). The weights are uncorrelated with the variables and thus do not effect the results, in this case.[21]

The final set of regressions are OLS regression with both month and firm dummies included (i.e. within estimates). I estimated White standard errors as well as Rogers standard errors clustered by firm or month. The lesson from these results is the same as before. Clustering by firm does not change the standard errors, but clustering by time leads to a significant, although smaller, increase in the standard errors (52 to 229 percent larger).[22]

B) Corporate Finance Application.

For the corporate finance illustration, I used a capital structure regression. The independent variables are those which are common from the literature (firm size, firm age, asset tangibility, and

[21] More sophisticated weighting schemes should be able to improve the efficiency of Fama-MacBeth estimates. However such estimators can be unstable in small samples (see Skoulakis, 2005).

[22] The coefficients change significantly when I include the firm dummies. For example, the coefficient on the log(share issuance) falls by forty percent. Thus variation in a firm's share issuance in a given year relative to the firm's average share issuance (which is what the within coefficient of -0.29 is measuring) has a smaller effect on returns than differences in average share issuance across firms (which is what the between coefficient of -0.97 is measuring, regression not reported). For a discussion of within and between estimates see Wooldridge, Chapter 10, 2002.

firm profitability). I lagged the independent variables one year relative to the dependent variable, used a long sample (1965-2003), and excluded firms which did not pay a dividend as in Fama and French (2002). The results are reported in Table 9.

The relative importance of the firm effect and the time effect can be seen by comparing the standard errors across the first three columns. The Rogers standard errors clustered by firm are dramatically larger than the White standard errors (1.8 to 2.3 times larger, see columns I and II). For example, the t-statistic on the advertising to sales ratio is -1.9 when I use the White standard errors and -0.7 when I use the Rogers standard errors clustered by firm. It is not surprising that R&D expenditure is highly persistent, and thus the auto-correlation for R&D expenditure is extremely high and persistent (see Figure 9). However, the auto-correlation in the residuals is also high and even after 12 years it remains above 40 percent.

The importance of the time effect (after including time dummies) is generally much smaller in this data set than in the previous one. The Roger's standard errors clustered by time are generally larger than the White standard errors but the magnitude of the difference is not large (except for the market to book ratio). This is due to a smaller auto-correlation in the residuals (see Figure 10). When I sorted by year, industry, and then firm, the residual first-order auto-correlation is less than 12 percent. The market to book standard error is the only one to increase dramatically and this occurs because of the large non-constant time effect discussed above.

These results also point out that the adjustment in the standard error can differ across variables in both sign and magnitude. Relative to the Roger's standard errors clustered by year, the White standard errors overstate the standard error on the "R&D is positive" dummy by 12 percent and understate the standard error on the market to book ratio by 64%. As long as the auto-correlation in the residuals is zero, then the White standard errors are correct. However, when the auto-correlation in the residuals is not zero, the bias in the standard errors will depend upon how the time pattern of the residual and independent variable auto-correlations interact (see footnote 4).

The Fama-MacBeth standard errors provide the same intuition as the Rogers standard errors clustered by time. In most cases, the Fama-MacBeth standard errors are quite close to the Rogers standard errors clustered by year and close to the White standard errors. Since dependence in the residual arises mostly from the firm effect, not the time effect, the bias in the Fama-MacBeth standard errors is similar to the bias in the OLS standard errors (compare equations 7 and 12). The only place where the standard error estimates differ is the advertising to sale ratio. The standard error on the advertising to sales ratio is not directly comparable, since the coefficient is not stable across models (see Table 9, columns III, IV, and V). The coefficient ranges from -0.0977 when estimated by OLS to 0.0747 when estimated by Fama-MacBeth. The weighted Fama-MacBeth estimate is -0.0002. The instability is consistent with the imprecision of our estimate. When we corrected the standard errors for a firm effect, the advertising to sales coefficient is no longer statistically different from zero.

VII) Conclusions.

It is well known from first-year econometrics classes that OLS standard errors are biased when the residuals are not independent. It has been less clear how financial researchers should estimate standard errors when using panel data sets. The empirical finance literature has proposed and used a variety of methods for estimating standard errors when the residuals are correlated across firms or years in the data. In this paper, I find that the performance of the different methods varies considerably and their relative accuracy depends upon the structure of the data. Simply put, estimates which are robust to the form of dependence in the data produce unbiased standard errors and correct confidence intervals; estimates which are not robust to the form of dependence in the data produced biased standard errors and often produce confidence intervals which are too small.

In the presence of a firm effect [e.g. $Cov(X_{i,t}\, \varepsilon_{i,t}, X_{i,t-k}\, \varepsilon_{i,t-k}) \neq 0$], Rogers standard errors (clustered by firm) are more accurate than standard errors estimated by OLS, Newey-West (modified for panel data sets), Fama-MacBeth, or Fama-MacBeth corrected for first-order auto-correlation.[23] The Rogers estimates (when clustered by firm) produce unbiased standard errors and correctly sized confidence intervals in the presence of a firm, whether the effect is permanent or temporary. When the firm effect is temporary, the Rogers standard errors are also superior to a fixed effect model.

In the presence of a time effect [e.g. $Cov(X_{i,t}\, \varepsilon_{i,t}, X_{i,t-k}\, \varepsilon_{i,t-k}) \neq 0$], Fama-MacBeth produce unbiased standard errors and correctly sized confidence intervals. This is not surprising since it was designed for a setting where residuals were correlated within a year, not across firms. Rogers standard errors (clustered by time) also produce unbiased standard errors and correctly sized confidence intervals, when there are a sufficient number of clusters. When there are too few clusters, Rogers standard errors are biased even when clustered on the correct dimension (see Figure 5).

None of the methods for estimating standard errors which I discussed are designed to deal with a firm and a time effect simultaneously. When both a firm and a time effect are present in the data, researchers need to address one parametrically (for example by including time dummies). The techniques discussed in the paper can then be applied. This raises the question of how researchers

[23] Skoulakis (2005) proposes applying the logic of Fama-MacBeth to each firm, instead of each year. He demonstrates that running N time series regressions and using the standard deviation of the N coefficients produces an estimate which is correct in the presence of a firm effect. I found only one paper in the literature which has used the Fama-MacBeth approach in this way (Coval and Shumway, 2005).

can determine what form of dependence may exist in the data and was the purpose of the two applications I examined in Section VI. By comparing the different standard errors, we can quickly observe the presence and general magnitude of a firm or a time effect. As we saw in Section VI, when the Rogers standard errors clustered by firm are much larger than the White standard errors, this indicated the presence of a firm effect in the data (the corporate finance application). When the Rogers standard errors clustered by time are much larger than the White standard errors this indicated the presence of a time effect in the data (the asset pricing application). Although firm effects seem to be more prevalent in corporate finance applications and time effects in asset pricing applications, this may not be a general rule, and thus the researcher must consult the data. This knowledge can provide researchers with intuition as to the deficiency of their models and provide suggestions for improving their models.

Appendix I: Data Set Constructions

A) Asset Pricing Application.

The data for the regressions in Table 8 are taken from Daniel and Titman's paper "Market Reactions to Tangible and Intangible Information" (2004). A more detailed description of the data can be found in their paper. The dependent variable is monthly returns on individual stocks from July, 1968 to December, 2001. The independent variables are:

Log(Lagged book to market) is the log of the total book value of the equity at the end of the firm's fiscal year ending anywhere in year t-6 divided by the total market equity on the last trading day of calendar year t-6.

Log(Book return) measures changes in the book value of the firm's equity over the previous five years. It is calculated as the log of one plus the percentage change in book value over the past five years. Thus if you purchased one percent of book value five years ago, and neither invested additional cash or nor took any cash out of the investment, book return is the current percentage ownership divided by the initial one percent.

Log(Market return) measures changes in the market value of the firm over the previous five years. It is calculated as the log of one plus the market return from the last day of year t-6 to the last day of year t-1.

Share issuance is a measure of net equity issuance. It is calculated as minus the log of the percentage ownership at the end of five years, assuming the investor started with 1 percent of the firm. Thus if investor purchases 1 percent of the firm and five years later they own 0.5 percent of the firm, then share issuance is equal to -log(0.5/1.0) = 0.693. Investors are assumed to neither take money out of their investment nor add additional money to their investment. Thus any cash flow which investors receive (e.g. dividends) would be reinvested. For transactions such as equity issues and repurchases, the investor is assumed not to participate and thus these will lower or raise the investor's fractional ownership.

To make sure that the accounting information is available to implement a trading strategy, the independent variables are lagged at least six months. Thus the independent variables for a fiscal year ending anytime during calendar year t-1, are used to predict future monthly returns from July of year t through June of year t+1. The independent variables are annual measures and are thus constant for each of the twelve monthly observations during the following year (July through June).

B) Corporate Finance Application

The data for the regressions in Table 9 are constructed from Compustat and include data from 1965 to 2003 (the dependent variable). The dependent variable, the market debt ratio, is defined as the book value of debt (data9 + data34) divided by the sum of the book value of assets (data6) minus the book value of equity (data60) plus the market value of equity (data25 * data199). The independent variables are lagged one year and I only include observations where the firm paid a dividend (data21) in the previous year (Fama and French, 2002). To reduce the influence of outliers, I capped ratio variables (e.g. profits to sales, tangible assets, advertising to sales, and R&D to sales) at the one and 99th percentile (Petersen and Faulkender, 2004, and Richardson and Sloan, 2003). The independent variables are:

Ln(Market Value of Assets) is the log of the sum of the book value of assets (data6) minus the book value of equity (data60) plus the market value of equity (data25 * data199).

Ln(1 + Firm Age). Firm age is calculated as the number of years the firm's stock has been listed. Firm age is calculated as the current year (fyenddt) minus the year the stock began trading (linkdt).

Profits / Sales is defined as operating profits before depreciation (data13) divided by sales revenue (data12).

Tangible assets is defined as property, plant, and equipment (data8) divide by the book value of total assets (data6).

Advertising / Sales is defined as advertising expense (data45) divided by sales (data12).

R&D / Sales is defined as R&D expenditure (data46) divided by sales (data12). If R&D is missing, it is coded as zero.

R&D > 0 is a dummy variable equal to one if R&D expenditure is positive, and zero otherwise.

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Table 1: Estimating Standard Errors with a Firm Effect
OLS and Rogers Standard Errors

Avg(β_{OLS}) Std(β_{OLS}) Avg(SE_{OLS}) Avg(SE_R)		Source of Independent Variable Volatility			
		0%	25%	50%	75%
Source of Residual Volatility	0%	1.0004 0.0286 0.0283 0.0283	1.0006 0.0288 0.0283 0.0282	1.0002 0.0279 0.0283 0.0282	1.0001 0.0283 0.0283 0.0282
	25%	1.0004 0.0287 0.0283 0.0283	0.9997 0.0353 0.0283 0.0353	0.9999 0.0403 0.0283 0.0411	0.9997 0.0468 0.0283 0.0463
	50%	1.0001 0.0289 0.0283 0.0282	1.0002 0.0414 0.0283 0.0411	1.0007 0.0508 0.0283 0.0508	0.9993 0.0577 0.0283 0.0590
	75%	1.0000 0.0285 0.0283 0.0282	1.0004 0.0459 0.0283 0.0462	0.9995 0.0594 0.0283 0.0589	1.0016 0.0698 0.0283 0.0693

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. The fraction of the residual variance which is due to a firm specific component is varies across the rows of the table from 0% (no firm effect) to 75%. The fraction of the independent variable's variance which is due to a firm specific component varies across the columns of the table from 0% (no firm effect) to 75%. Each cell contains the average slope coefficient estimated by OLS and the standard deviation of this estimate. This is the true standard error of the estimated coefficient. The third entry is the average OLS estimated standard error of the coefficient. The fourth entry is the average Rogers (clustered) standard error which accounts for possible clustering at the firm level (i.e. accounts for the possible correlation between observations of the same firm in different years). As an example, when fifty percent of the variability in both the residual and the independent variable is due to the fixed firm effect ($\rho_X = \rho_\varepsilon = 0.50$), the true standard error of the OLS coefficient is 0.0508. The OLS standard error estimate is 0.0283 and the Rogers standard error estimate is 0.0508.

Table 2: Estimating Standard Errors with a Firm Effect
Fama-MacBeth Standard Errors

Avg(β_{FM}) Std(β_{FM}) Avg(SE_{FM})		Source of Independent Variable Volatility			
		0%	25%	50%	75%
Source of Residual Volatility	0%	1.0004 0.0287 0.0276	1.0006 0.0288 0.0276	1.0002 0.0280 0.0277	1.0001 0.0283 0.0275
	25%	1.0004 0.0288 0.0275	0.9997 0.0354 0.0268	0.9998 0.0403 0.0259	0.9997 0.0469 0.0250
	50%	1.0000 0.0289 0.0276	1.0002 0.0415 0.0259	1.0007 0.0509 0.0238	0.9993 0.0578 0.0219
	75%	1.0000 0.0286 0.0277	1.0004 0.0460 0.0248	0.9995 0.0595 0.0218	1.0016 0.0699 0.0183

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. The fraction of the residual variance which is due to a firm specific component is varied across the rows of the table from 0% (no firm effect) to 75%. The fraction of the independent variable's variance which is due to a firm specific component is varies across the columns of the table from 0% (no firm effect) to 75%. The first entry is the average estimated slope coefficient based on a Fama-MacBeth estimation (e.g. I ran the regression for each of the 10 years and took the average). The second entry is the standard deviation of the coefficient estimated by Fama-MacBeth. This is the true standard error of the Fama-MacBeth coefficient. The third entry is the average standard error estimated by the Fama-MacBeth procedure (see equation 9). As an example, when fifty percent of the variability in both the residual and the independent variable is due to the fixed firm effect ($\rho_X = \rho_\varepsilon = 0.50$), the true standard error of the Fama-MacBeth coefficient is 0.0509. The Fama-MacBeth standard error estimate is 0.0238.

Table 3: Estimating Standard Errors with a Time Effect
OLS and Rogers Standard Errors

Avg(β_{OLS}) Std(β_{OLS}) Avg(SE_{OLS}) Avg(SE_R)		Source of Independent Variable Volatility			
		0%	25%	50%	75%
Source of Residual Volatility	0%	1.0004 0.0286 0.0283 0.0277	1.0002 0.0291 0.0288 0.0276	1.0006 0.0293 0.0295 0.0275	0.9994 0.0314 0.0306 0.0270
	25%	1.0006 0.0284 0.0279 0.0268	1.0043 0.1490 0.0284 0.1297	0.9962 0.2148 0.0289 0.1812	0.9996 0.2874 0.0300 0.2305
	50%	0.9996 0.0276 0.0274 0.0258	0.9997 0.2138 0.0278 0.1812	0.9919 0.3015 0.0282 0.2546	1.0079 0.3986 0.0292 0.3248
	75%	1.0002 0.0273 0.0267 0.0244	0.9963 0.2620 0.0271 0.2215	0.9970 0.3816 0.0276 0.3141	0.9908 0.4927 0.0284 0.3986

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. The fraction of the residual variance which is due to a year specific component varies across the rows of the table from 0 percent (no time effect) to 75 percent. The fraction of the independent variable's variance which is due to a year specific component varies across the columns of the table from 0 percent (no time effect) to 75 percent. Each cell contains the average estimated slope coefficient from OLS and the standard deviation of this estimate. This is the true standard error of the estimated coefficient. The third entry is the average standard error estimated by OLS. The fourth entry is the average Rogers (clustered) standard error which accounts for possible clustering by year (i.e. accounts for the possible correlation between observations on different firms in the same year).

Table 4: Estimating Standard Errors with a Time Effect
Fama-MacBeth Standard Errors

Avg(β_{FM}) Std(β_{FM}) Avg(SE_{FM})		Source of Independent Variable Volatility			
		0%	25%	50%	75%
Source of Residual Volatility	0%	1.0004 0.0287 0.0278	1.0004 0.0331 0.0318	1.0007 0.0396 0.0390	0.9991 0.0573 0.0553
	25%	1.0005 0.0252 0.0239	1.0003 0.0284 0.0276	1.0006 0.0343 0.0338	0.9999 0.0496 0.0480
	50%	1.0000 0.0200 0.0195	1.0002 0.0231 0.0227	1.0006 0.0280 0.0276	1.0007 0.0394 0.0387
	75%	1.0001 0.0142 0.0138	0.9996 0.0161 0.0159	1.0000 0.0200 0.0196	0.9999 0.0285 0.0276

Notes

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. The fraction of the residual variance which is due to a year specific component varies across the rows of the table from 0 percent (no time effect) to 75 percent. The fraction of the independent variable's variance which is due to a year specific component varies across the columns of the table from 0 percent (no time effect) to 75 percent. The first entry is the average estimated slope coefficient based on a Fama-MacBeth estimation (e.g. the regression is run for each of the 10 years and the estimate is the average of the 10 estimated slope coefficients). The second entry is the standard deviation of the coefficient estimated by Fama-MacBeth. This is the true standard error of the Fama-MacBeth coefficient. The third entry is the average standard error estimated by the Fama-MacBeth procedure (e.g. equation 9).

Table 5: Estimating Standard Errors with a Firm and Time Effect
OLS and Rogers Standard Errors

Avg(β_{OLS}) Std(β_{OLS}) Avg(SE_{OLS}) Avg(SE_R)		Independent Variable Volatility from Firm Effect		
		25%	25%	50%
		Independent Variable Volatility from Time Effect		
		25%	50%	25%
Residual Volatility from Firm Effect	**Residual Volatility from Time Effect**			
25%	25%	0.9997 0.0407 0.0283 0.0400	1.0004 0.0547 0.0347 0.0548	1.0004 0.0489 0.0283 0.0489
25%	50%	1.0005 0.0362 0.0231 0.0364	1.0015 0.0515 0.0283 0.0508	0.9993 0.0468 0.0231 0.0461
50%	25%	1.0002 0.0493 0.0283 0.0490	1.0008 0.0690 0.0347 0.0692	0.9994 0.0631 0.0283 0.0630

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set with 5,000 observations (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. In these simulations, the proportion of the variance of the independent variable and the residual which is due to the firm effect is either 25 or 50 percent. The proportion which is due to the time effect is also 25 or 50 percent. For example, in the bottom left cell 25 percent of the variability in the independent variable is from the firm effect and 25 percent is from the time effect. 50 percent of the variability of the residual is from the firm effect and 25 percent is from the time effect. Each cell contains the average estimated slope coefficient from OLS and the standard deviation of this estimate. This is the true standard error of the estimated coefficient. The third entry is the average standard error estimated from OLS. The fourth entry is the average Rogers (clustered) standard error which accounts for possible clustering at the firm level (i.e. accounts for the possible correlation between observations of the same firm in different years). Each regression includes nine year dummies.

Table 6: Estimating Standard Errors with a Firm and Time Effect
Fama-MacBeth Standard Errors

Avg(β_{FM}) Std(β_{FM}) Avg(SE_{FM})				Independent Variable Volatility from Firm Effect		
				25%	25%	50%
				Independent Variable Volatility from Time Effect		
				25%	50%	25%
Residual Volatility from Firm Effect	25%	Residual Volatility from Time Effect	25%	0.9997 0.0407 0.0258	1.0004 0.0547 0.0309	1.0004 0.0489 0.0243
	25%		50%	1.0005 0.0362 0.0206	1.0015 0.0515 0.0239	0.9993 0.0469 0.0185
	50%		25%	1.0002 0.0493 0.0244	1.0008 0.0691 0.0275	0.9994 0.0632 0.0206

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set with 5,000 observations (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. In these simulations, the proportion of the variance of the independent variable and the residual which is due to the firm effect is either 25 or 50 percent. The proportion which is due to the time effect is also 25 or 50%. For example, in the bottom left cell 25 percent of the variability in the independent variable is from the firm effect and 25 percent is from the time effect. 50 percent of the variability of the residual is from the firm effect and 25 percent is from the time effect. The first entry in each cell is the average estimated slope coefficient based on a Fama-MacBeth estimation (e.g. I ran the regression for each of the 10 years and took the average). The second entry is the standard deviation of this coefficient. This is the true standard error of the Fama-MacBeth coefficient. The third entry is the average standard error estimated by the Fama-MacBeth procedure (e.g. equation 9).

Table 7: Estimated Standard Errors with a Non-Fixed Firm Effect
Panel A: OLS and Rogers Standard Errors

Avg(β_{OLS}) Std(β_{OLS}) Avg(SE_{OLS}) Avg(SE_R)	I	II	III	IV
ρ_X / ρ_ε	0.25 / 0.25	0.00 / 0.00	0.25 / 0.25	0.50 / 0.50
φ_X / φ_ε	0.00 / 0.00	0.75 / 0.75	0.75 / 0.75	0.50 / 0.50
OLS	1.0001 0.0355 0.0283 0.0352	1.0001 0.0483 0.0283 0.0488	1.0009 0.0566 0.0283 0.0569	1.0007 0.0587 0.0283 0.0578
OLS with firm dummies	1.0007 0.0299 0.0298 0.0314	1.0008 0.0443 0.0298 0.0466	1.0013 0.0442 0.0298 0.0465	1.0000 0.0357 0.0298 0.0377

Panel B: Fama-MacBeth Standard Errors

Avg(β_{FM}) Std(β_{FM}) Avg(SE_{FM}) Avg(SE_{FM-AR1})	I	II	III	IV
ρ_X / ρ_ε	0.25 / 0.25	0.00 / 0.00	0.25 / 0.25	0.50 / 0.50
φ_X / φ_ε	0.00 / 0.00	0.75 / 0.75	0.75 / 0.75	0.50 / 0.50
Fama-MacBeth	1.0001 0.0357 0.0267 0.0250 0.0250	1.0001 0.0484 0.0240 0.0374 0.0344	1.0008 0.0567 0.0221 0.0376 0.0336	1.0007 0.0588 0.0220 0.0296 0.0281
Avg(1st order auto-correlation)	-0.1134	0.2793	0.3250	0.1759

Notes:

The table contains estimates of the coefficient and standard errors based on 5,000 simulation of a panel data set with 5,000 observations (10 years per firm and 500 firms). The true slope coefficient is 1, the standard deviation of the independent variable is 1 and the standard deviation of the error term is 2. Across the columns the magnitude of the fixed firm effect (ρ) and the first order auto-correlation (φ) is changed. ρ_X (ρ_ε) is the fraction of the independent variable's (residual's) variance which is due to the fixed firm effect. φ_x (φ_ε) is the first order auto-correlation of the non-fixed portion of the firm effect of the independent variable (the residual). Combining equations (4) and (5) with equation (16), the residual is specified as:

$$\begin{aligned} \varepsilon_{it} &= \mu_{it} + \eta_{it} = \mu_{it} + \varsigma_{it} && \text{if } t = 1 \\ &= \mu_{it} + \eta_{it} = \mu_{it} + \varphi_\varepsilon \eta_{it-1} + \sqrt{1 - \varphi^2}\, \varsigma_{it} && \text{if } t > 1 \end{aligned} \quad \textbf{(1)}$$

The independent variable is specified in a similar manner.

Panel A contains coefficients estimated by OLS. In the first row only the independent variable (X) is included; in the second row 499 firm dummies (for 500 firms) are also included in the regression. The first two entries in each cell contain the average slope estimated by OLS and the standard deviation of the coefficient (i.e. the true standard error). The third entry is the average standard error estimated from OLS. The fourth entry is the average Rogers (clustered) standard error which accounts for possible clustering at the firm level (i.e. accounts for the possible correlation between observations of the same firm in different years).

Panel B contains coefficients and standard errors estimated by Fama-MacBeth. The first two entries in each cell contain the average slope estimated by Fama-MacBeth and the standard deviation of the coefficient (i.e. the true standard error). The third entry in these cells is the average standard error estimated by the Fama-MacBeth procedure (see equation 9). The last two entries are the average Fama-MacBeth standard error estimate corrected for first order auto-correlation. The fourth entry assumes an infinite lag (i.e. multiplied by the square root of (1+φ)/(1-φ)), and the fifth entry assumes a finite lag of 9 periods (i.e. multiply by the square root of sum from k=1 to T of (T-k) φ^k). The bottom row contains the average across the 5,000 simulation of the first order autocorrelation of β_t and β_{t-1} estimated within each of the 5,000 samples.

Table 8: Asset Pricing Application
Equity Returns and Asset Tangibility

	I	II	III	IV	V	VI	VII	VIII
Log(B/M_{t-5})	0.1883[1]	0.1883[1]	0.1883[10]	0.1728[5]	0.1504[10]	1.1277[1]	1.1277[1]	1.1277[1]
	(0.0261)	(0.0270)	(0.1007)	(0.0824)	(0.0831)	(0.0476)	(0.0542)	(0.1135)
Log(Book Return)	0.1946[1]	0.1946[1]	0.1946[5]	0.1691[5]	0.1544[10]	0.5885[1]	0.5885[1]	0.5885[1]
(last 5 years)	(0.0421)	(0.0433)	(0.0973)	(0.0848)	(0.0808)	(0.0523)	(0.0568)	(0.1038)
Market Return	-0.3177[1]	-0.3177[1]	-0.3177[1]	-0.3002[1]	-0.2536[1]	-1.2275[1]	-1.2275[1]	-1.2275[1]
(last 5 years)	(0.0283)	(0.0292)	(0.1092)	(0.0957)	(0.0910)	(0.0377)	(0.0437)	(0.1242)
Share issuance	-0.5012[1]	-0.5012[1]	-0.5012[1]	-0.5172[1]	-0.5104[1]	-0.2942[1]	-0.2942[1]	-0.2942[1]
	(0.0471)	(0.0466)	(0.1529)	(0.1275)	(0.1213)	(0.0623)	(0.0718)	(0.0949)
R^2	0.0006	0.0006	0.0006	0.0006	0.0006	0.0191	0.0191	0.0191
Coefficient Estimates	OLS	OLS	OLS	FM	WFM	OLS	OLS	OLS
Standard Errors	White	Rogers (F)	Rogers (T)	FM	FM	White	Rogers (F)	Rogers (T)
Dummies	T	T	T			F & T	F & T	F & T

Notes:

The table contains coefficient and standard error estimates of the equity return regressions from Daniel and Titman (2004). The data is briefly described in the appendix and in detail in their paper. The sample runs from July, 1968 to December, 2001 and contains 699,707 firm-month observations. The estimates in columns I-III and VI-VII are OLS coefficients. All six regressions contain time (monthly) dummies and the last three columns contain firm dummies as well (see the last row of the table). Standard errors are reported in parenthesis. I report White standard errors in columns I and VI, Rogers standard errors clustered by firm in columns II and VII and Rogers standard errors clustered by month in columns III and VIII. Column IV and V contain coefficients and standard errors estimated by Fama-MacBeth. In column V, I weighted each of the monthly coefficient estimates by the number of observations in the given month.

[10] significant at 10%; [5] significant at 5%; [1] significant at 1%

Table 9: Corporate Finance Application
Capital Structure Regressions (1965-2003)

	I	II	III	IV	V	VI	VII	VIII
Ln(MV Assets)	0.0799[1]	0.0799[1]	0.0799[1]	0.0808[1]	0.0788[1]	-0.0619[5]	-0.0619	-0.0619[5]
	(0.0042)	(0.0130)	(0.0055)	(0.0054)	(0.0052)	(0.0252)	(0.0400)	(0.0287)
Ln(1+Firm Age)	-0.0806[1]	-0.0806[1]	-0.0806[1]	-0.0841[1]	-0.0821[1]	0.1948[1]	0.1948[5]	0.1948[5]
	(0.0069)	(0.0229)	(0.0069)	(0.0094)	(0.0083)	(0.0707)	(0.0923)	(0.0744)
Profits / Sales	-0.0798[1]	-0.0798[1]	-0.0798[1]	-0.0757[1]	-0.0781[1]	-0.5757[1]	-0.5757[1]	-0.5757[1]
	(0.0083)	(0.0253)	(0.0105)	(0.0095)	(0.0100)	(0.1324)	(0.1589)	(0.1550)
Tangible assets	0.1077[1]	0.1077[1]	0.1077[1]	0.1082[1]	0.1090[1]	0.2157[5]	0.2157[5]	0.2157[5]
	(0.0044)	(0.0137)	(0.0068)	(0.0064)	(0.0064)	(0.0849)	(0.0966)	(0.0946)
Market to book	-0.0267[1]	-0.0267[1]	-0.0267[1]	-0.0289[1]	-0.0282[1]	-0.0242[1]	-0.0242[5]	-0.0242[1]
(Assets)	(0.0005)	(0.0016)	(0.0014)	(0.0018)	(0.0017)	(0.0085)	(0.0112)	(0.0086)
Advertising / Sales	-0.0977[10]	-0.0977	-0.0977[10]	0.0747	-0.0002	0.1561	0.1561	0.1561
	(0.0499)	(0.1401)	(0.0559)	(0.1594)	(0.1221)	(1.0263)	(0.9953)	(1.1532)
R&D / Sales	-0.3782[1]	-0.3782[1]	-0.3782[1]	-0.2792[1]	-0.2980[1]	-2.4157[5]	-2.4157[10]	-2.4157[10]
	(0.0371)	(0.1128)	(0.0545)	(0.0720)	(0.0616)	(0.9813)	(1.4197)	(1.2721)
R&D > 0	0.0306[1]	0.0306[1]	0.0306[1]	0.0288[1]	0.0303[1]	-0.0440	-0.0440	-0.0440
(=1 if yes)	(0.0019)	(0.0055)	(0.0017)	(0.0020)	(0.0019)	(0.0404)	(0.0479)	(0.0458)
R-squared	0.1289	0.1289	0.1289	0.1232	0.1238	0.6730	0.6730	0.6730
Coefficient Estimates	OLS	OLS	OLS	FM	WFM	OLS	OLS	OLS
Standard Errors	White	Rogers (F)	Rogers (T)	FM	FM	OLS	Rogers (F)	Rogers (T)

Dummies	T	T	T			F & T	F & T	F & T

Notes:

The table contains coefficient and standard error estimates of the capital structure regressions. The dependent variable is the market debt ratio (book value of debt divided by the sum of the book value of assets minus the book value of equity plus the market value of equity). The data is annual observations between 1965 and 2003 and contains 50,870 firm years. Only firms which pay a dividend in the previous year are included in the sample. The independent variables are lagged one year and are defined in the appendix. The estimates in columns I-III and VI-VII are OLS coefficients. All six regressions contain time (yearly) dummies and the last three columns contain firm dummies as well (see the last row of the table). Standard errors are reported in parenthesis. I report White standard errors in columns I and VI, Rogers standard errors clustered by firm in columns II and VII and Rogers standard errors clustered by year in columns III and VIII. Column IV and V contain coefficients and standard errors estimated by Fama-MacBeth. In column V, I weighted each of the yearly coefficient estimates by the number of observations in the given year.

[10] significant at 10%; [5] significant at 5%; [1] significant at 1%

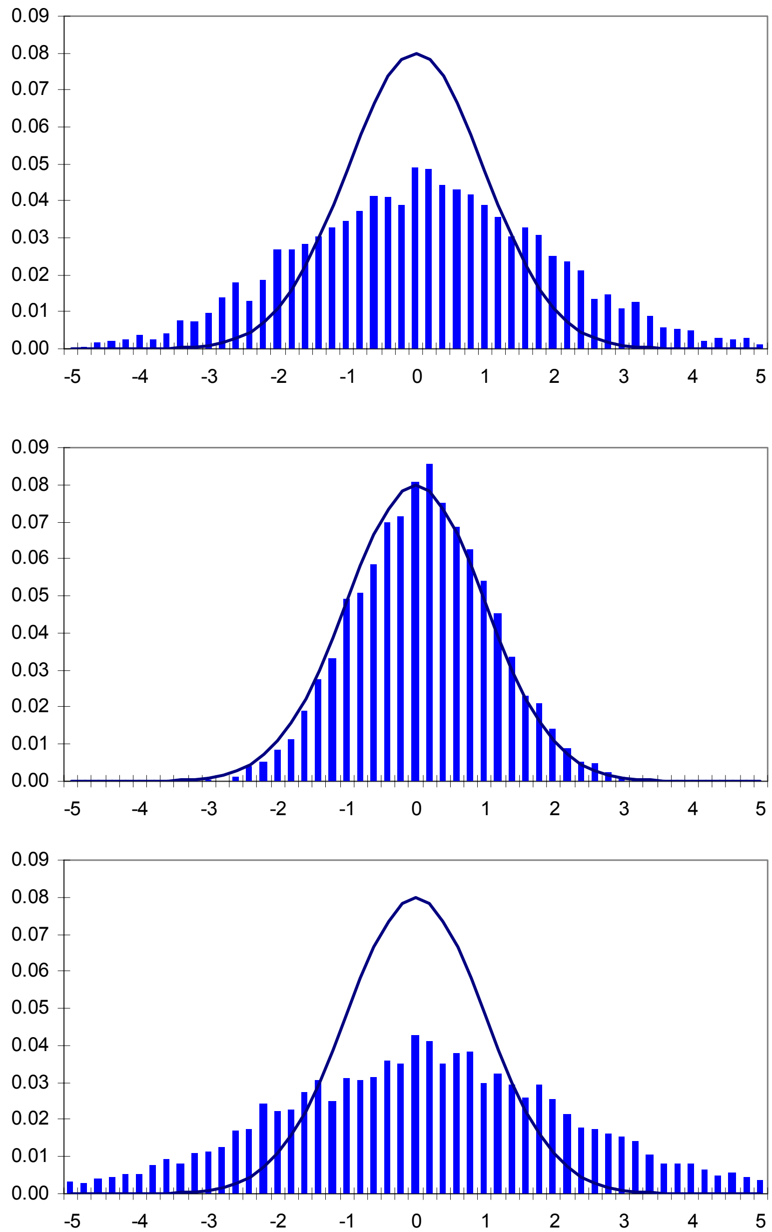
Figure 1: Residual Cross Product Matrix
Assumptions About Zero Co-variances

		Firm 1			Firm 2			Firm 3	
Firm 1	ϵ_{11}^2	$\epsilon_{11}\epsilon_{12}$	$\epsilon_{11}\epsilon_{13}$	0	0	0	0	0	0
	$\epsilon_{12}\epsilon_{11}$	ϵ_{12}^2	$\epsilon_{12}\epsilon_{13}$	0	0	0	0	0	0
	$\epsilon_{13}\epsilon_{11}$	$\epsilon_{13}\epsilon_{12}$	ϵ_{13}^2	0	0	0	0	0	0
Firm 2	0	0	0	ϵ_{21}^2	$\epsilon_{21}\epsilon_{22}$	$\epsilon_{21}\epsilon_{23}$	0	0	0
	0	0	0	$\epsilon_{22}\epsilon_{21}$	ϵ_{22}^2	$\epsilon_{22}\epsilon_{23}$	0	0	0
	0	0	0	$\epsilon_{23}\epsilon_{21}$	$\epsilon_{23}\epsilon_{22}$	ϵ_{23}^2	0	0	0
Firm 3	0	0	0	0	0	0	ϵ_{31}^2	$\epsilon_{31}\epsilon_{32}$	$\epsilon_{31}\epsilon_{33}$
	0	0	0	0	0	0	$\epsilon_{32}\epsilon_{31}$	ϵ_{32}^2	$\epsilon_{32}\epsilon_{33}$
	0	0	0	0	0	0	$\epsilon_{33}\epsilon_{31}$	$\epsilon_{33}\epsilon_{32}$	ϵ_{33}^2

Notes:

This figure shows a sample covariance matrix of the residuals. Assumptions about elements of this matrix and which are zero is the source of difference in the various standard error estimates. The covariance of the matrix of the residuals has $(NT)^2$ elements where N is the number of firms and T is the number of years. Both are three in this illustration. The standard OLS assumption is that only the NT diagonal terms are non-zero. Rogers standard errors clustered by firm assumes that the correlation of the residuals within the cluster may be non-zero (these elements are shaded). The cluster assumption assumes that residuals across clusters are uncorrelated. These are recorded as zero in the above matrix.

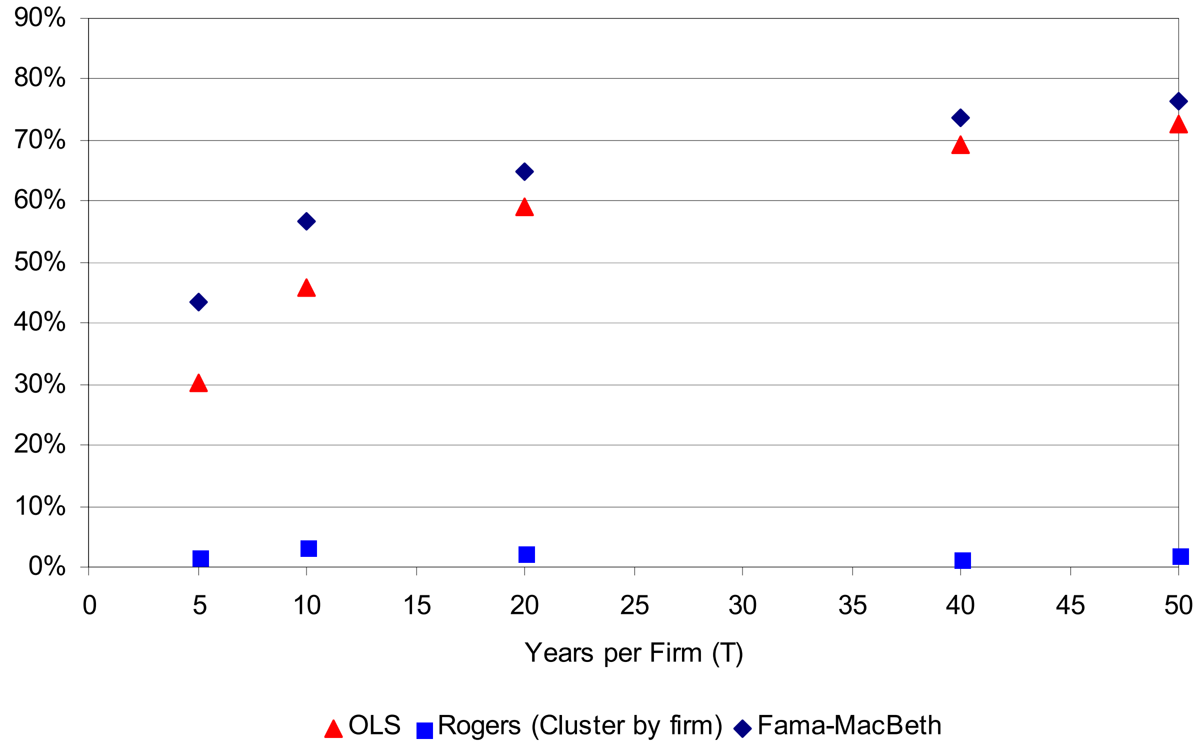
Figure 2: Distribution of Simulated T-Statistics



Notes:

The figures contain the theoretical t-distribution (the line), and the distribution of t-statistics produced by the simulation (the bars) when fifty percent of the variability in the independent variable and the residual is due to the firm effect. The top figure is the distribution of the t-statistics based on the OLS standard errors, the middle figure is the distribution of t-statistics based on the Rogers standard errors clustered by firm, and the bottom figure is the distribution of t-statistics based on the Fama-MacBeth standard errors. When the standard errors estimates are too small (as with OLS and Fama-MacBeth) there are too many t-statistics which are large in absolute value.

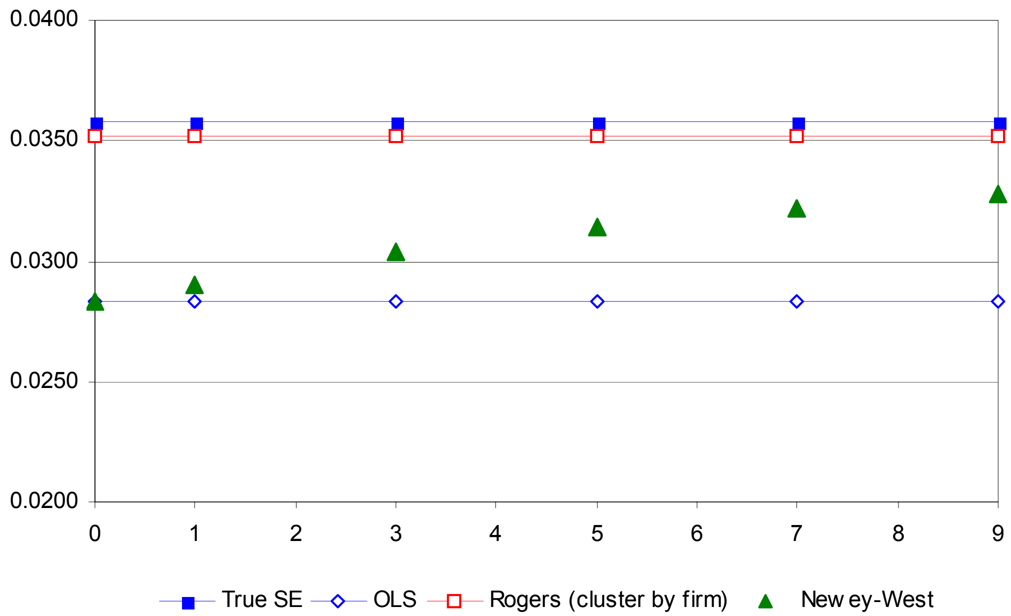
Figure 3: Bias in Estimated Standard Errors
As a function of observations per cluster



Notes:

The figure graphs the percentage by which the three methods underestimate the true standard error in the presence of a firm effect. The results are based on 5,000 simulations of a data set with 5,000 observations. The number of years per firm ranges from five to fifty. The firm effect was assumed to comprise fifty percent of the variability in both the independent variable and the residual. The underestimates are calculated as one minus the average standard error estimated by the method divided by the true standard deviation of the coefficient estimate. For example, the standard deviation of the coefficient estimate was 0.0406 in the simulation with five years of data (T=5). The average of the OLS estimated standard errors is 0.0283. Thus the OLS underestimated the true standard error by 30% (1 - 0.0283/0.0406).

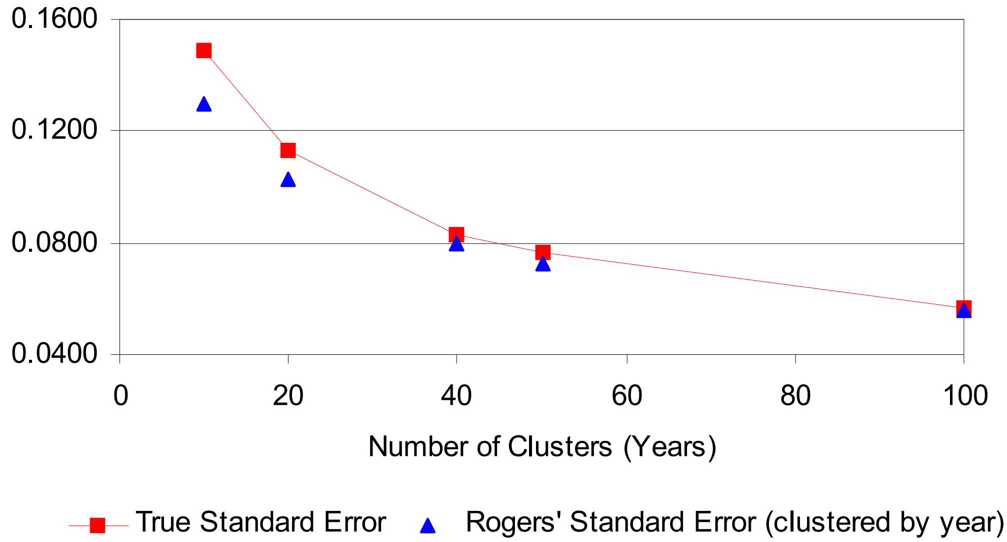
Figure 4: Relative Performance of OLS, Rogers, and Newey-West Standard Errors



Notes:

The figure contains OLS, Rogers (clustered by firm), and Newey-West standard error estimates, as well as the true standard error. Estimates are based on 5,000 simulated data sets. Each data set contains 5,000 observations (500 firms and 10 years for each firm). In each simulation, twenty-five percent of the variability in both the independent variable and the residual is due to a firm effect [i.e. $\rho_X = \rho_\varepsilon = 0.25$]. The true standard error (shaded squares), the OLS standard error estimates (empty diamonds), and the Rogers standard error estimates (empty squares) are plotted as straight lines as they do not depend upon the assumed lag length. The Newey-West standard error estimates, which rise with the assumed lag length, are plotted as triangles.

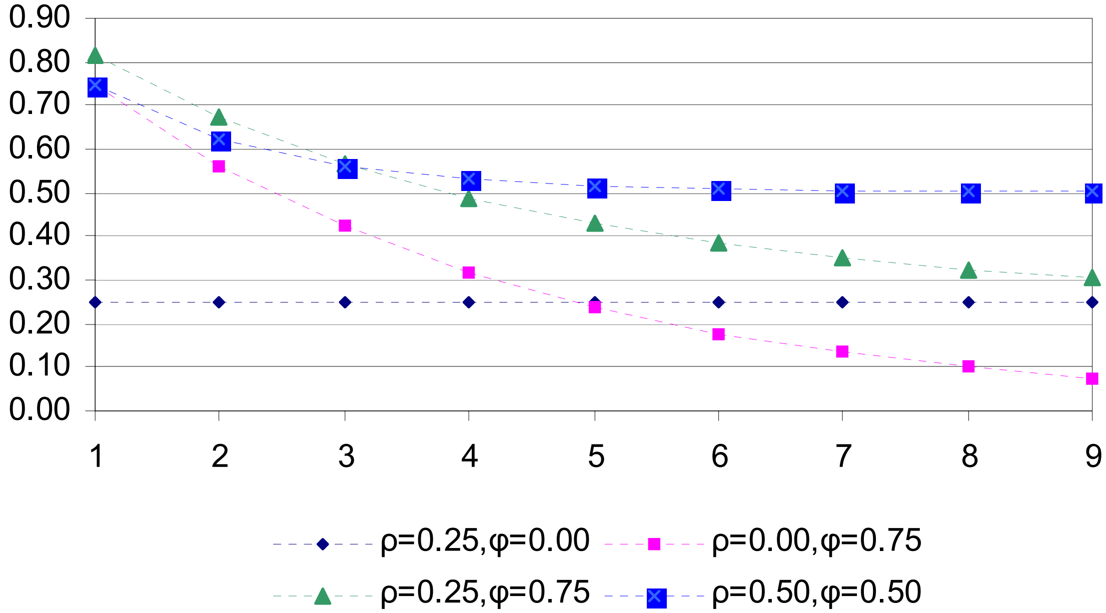
Figure 5: True Standard Errors and Robust Estimates
as a function of cluster size (T)



Notes:

The true standard errors (squares) and the Rogers standard error clustered by year (triangles) are graphed against the number of years (clusters) used in each simulation. The standard errors are the average across 5,000 simulations. Each simulated data set has 5,000 observations. In each simulation, twenty-five percent of the variability in both the independent variable and the residual is due to the time effect [i.e. $\rho_X = \rho_\varepsilon = 0.25$]. The robust estimates underestimate the true standard errors, but this underestimate declines with the number of years (clusters). In these simulations, the underestimation ranges from 15 percent when there were 10 years in the simulated data set to 1 percent when there were 100 years in the simulated data set.

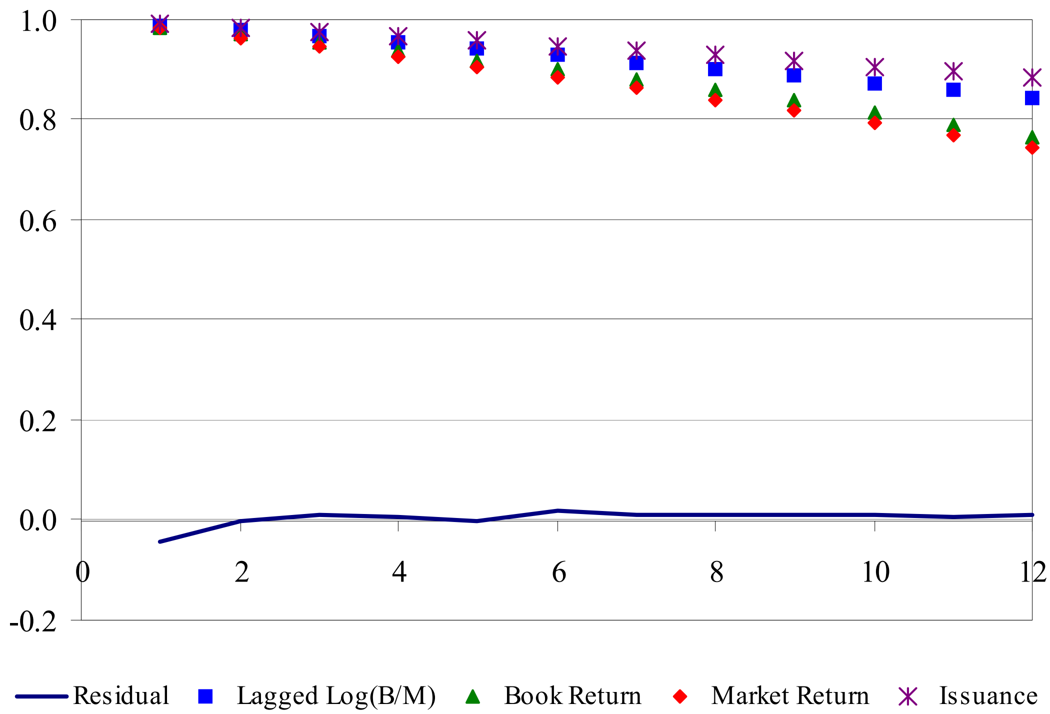
Figure 6: Auto-correlation Patterns of Non-Fixed Firm Effects



Notes:

This figure contains the auto-correlations of the residuals and the independent variable for lags one through nine for the data structures used in Table 7. The specifications contain a fixed and a temporary firm component. ρ is the fraction of the variance which is due to the fixed firm effect and φ is the first order auto-correlation of the non-fixed firm effect (see equation 17).

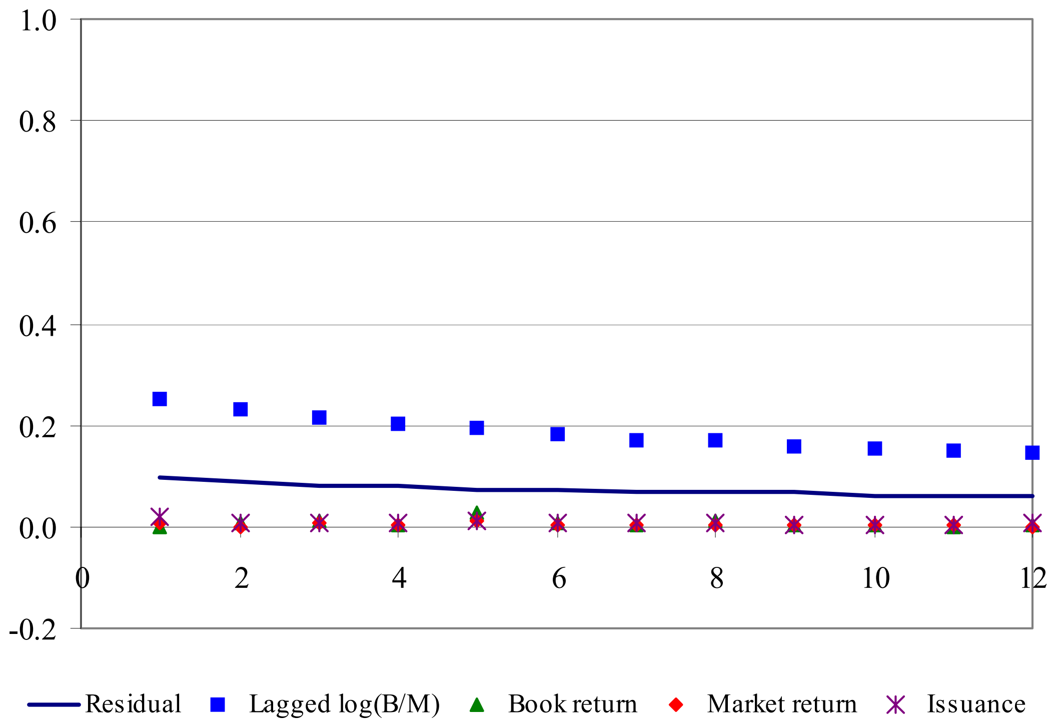
Figure 7: Within Firm Auto-Correlation in the Residuals and the Independent Variables
Asset Pricing Example



Notes:

The auto-correlations of the residual and the four independent variables are graphed for lags of one to twelve months. Correlations are calculate only for observations of the same firm [i.e. Corr ($\varepsilon_{i\,t}\,\varepsilon_{i\,t\text{-}k}$) for k equal one to twelve]. The independent variables are described in the appendix and in Daniel and Titman (2004).

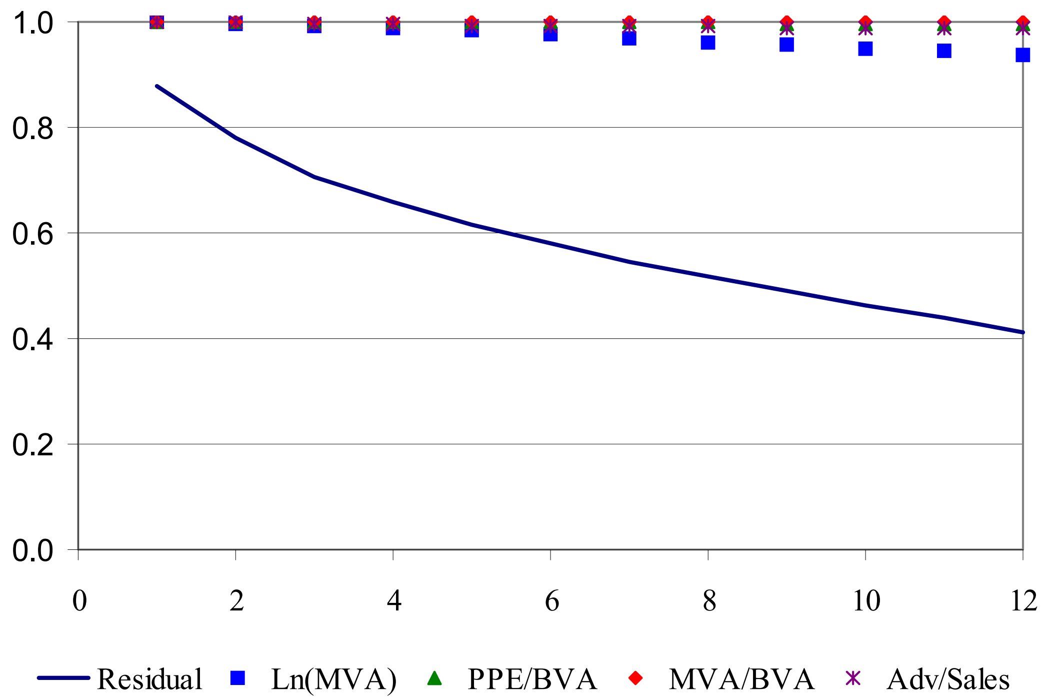
Figure 8: Within Month Auto-Correlation in the Residuals and the Independent Variables
Asset Pricing Example



Notes:

The auto-correlations of the residuals and the four independent variables are graphed for lags of one to twelve firms. Correlations are calculated only for observations of the same year [i.e. Corr ($\varepsilon_{it}\, \varepsilon_{i\text{-}kt}$) for k equal one to twelve]. The data was sorted by month, then by four digit industry, and then by firm identifier (permco). The independent variables are described in the appendix and in Daniel and Titman (2004).

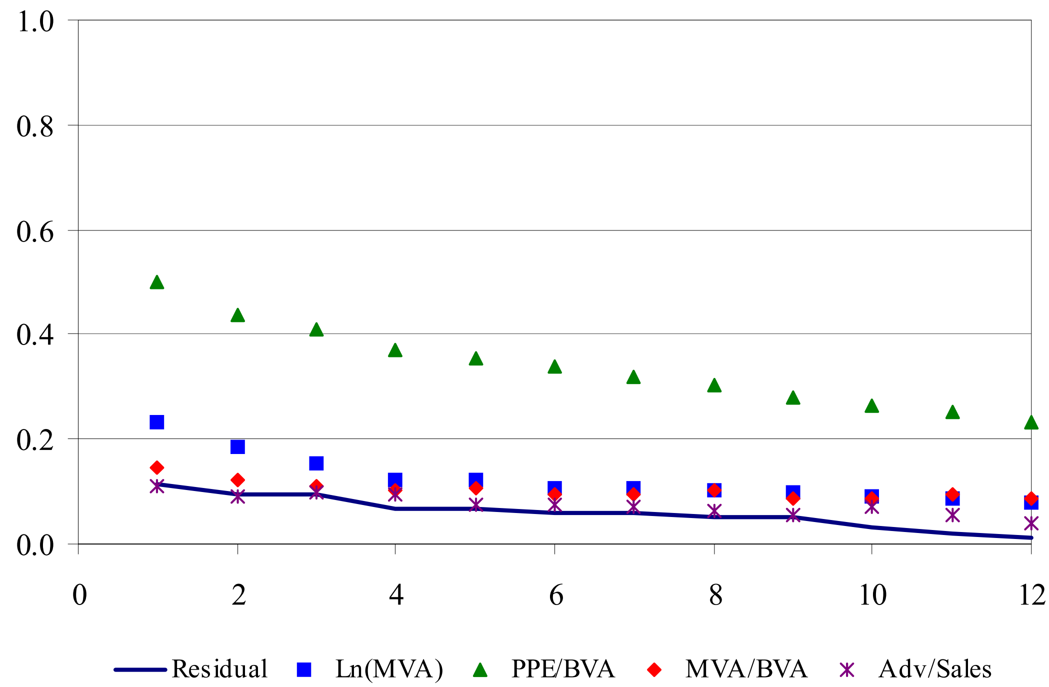
Figure 9: Within Firm Auto-Correlation in the Residuals and the Independent Variables
Corporate Finance Example



Notes:

The auto-correlations of the residual and four of the eight independent variables are graphed for lags of one to twelve years. Correlations are calculate only for observations of the same firm [i.e. Corr ($\varepsilon_{i\,t}\,\varepsilon_{i\,t\text{-}k}$) for k equal one to twelve]. The independent variables are described in the appendix. The graph for the remaining four variables are similar and are available from the author.

Figure 10: Within Month Auto-Correlation in the Residuals and the Independent Variables
Corporate Finance Example



Notes:

The auto-correlations of the residuals and four of the eight independent variables are graphed for lags of one to twelve firms. Correlations are calculated only for observations of the same year [i.e. Corr ($\varepsilon_{i\,t}\, \varepsilon_{i\text{-}k\,t}$) for k equal one to twelve]. The data was sorted by month, then by four digit industry, and then by firm identifier (gvkey). The independent variables are described in the appendix. The graph for the remaining four variables are similar and are available from the author.