Are International Equity Market Returns Predictable?

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September 2009

Abstract

The slope coefficient estimator in predictive regressions for stock returns is biased by a lagged stochastic regressor. There is also a spurious regression if the underlying expected return is highly persistent. This paper studies how the interactions between the two biases affect inferences about the predictability in international equity market returns. The analysis considers how the biases work in the presence of data mining for the predictive variables. I find that the two biases can reinforce or offset each other, depending on the parameters of the model. I present a new correction for the bias in the presence of both effects and evaluate its economic significance. Adjusting for data mining associated with both effects, I find that many of the global predictors have a weak explanatory power when they are individually regressed for the world market return and that 8 of the 18 national equity market returns may have at least one significant predictive variable after the apparent number of searches are accounted for.

[*]I am very much indebted to Wayne Ferson for the development of research idea and ongoing support. I am also grateful to Guido Kuersteiner, Pierre Perron, Zhongjun Qu and seminar participants at Boston University, the Sixteenth Annual PBFEA Conference, the 2008 Asian FA-NFA Conference in Yokohama and the 2009 FMA European Conference in Turin. I acknowledge the financial support from Boston University's special research fellowship for Spring 2007. All remaining errors are solely mine.

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In the literature about international stock return predictability, the choice of predictive variables is greatly influenced by the evidence from U.S. data. While some authors like Ferson and Harvey (1993, 1994, 1997) and Rapach, Wohar, and Rangvid (2005) examine a broad set of macro-economic or firm-specific variables concurrently, many studies of non-U.S. market returns employ predictive variables known for possessing explanatory power to forecast U.S. stock returns, such as dividend yields, short-term interest rates, default spreads, and term structure variables.

Many of these predictors are highly autocorrelated and are likely to be correlated with predictive regression disturbances. When such regressors are employed, biases may appear in the conventional regression statistics. On the other hand, there are data mining concerns raised by several researchers for the predictive regressions, particularly because the left-hand stock return series are generally overlapping over different regression specifications while there are few theories explicit about the "correct" predictive variables. For example, if there is a country portfolio whose return comoves with the U.S. stock return and a variable has been data-mined to predict the U.S. stock return, the same variable may appear to have an explanatory power for the country portfolio's return (Foster, Smith, and Whaley (1997)). However, little is known about how these biases interact and, thereby, affect statistical inferences in the international context.

This paper re-evaluates return predictability in international equity markets. In particular, I focus on the interaction of three important problems in evaluating the ability of lagged variables to predict stock returns. The three problems are spurious regression, data mining, and 'lagged stochastic regressor bias' suggested by Mankiw and Shapiro (1986) and Stambaugh (1986, 1999).

Spurious regression refers to the failure of conventional test procedures in regressions involving highly persistent time series. While most theoretical work highlights nonstationary models in which variables are modeled as a unit root or nearly integrated process, Ferson, Sarkissian, and Simin (2003) find that spurious relations can appear in stock return regressions where the left-hand side returns are not highly persistent, if there exist time-varying risk premiums that are highly persistent over time.[1]

Lagged stochastic regressor bias arises when the predictive regression disturbance is correlated

[1] There are recent discussions of spurious regression problems in forecasting stock returns when the predictors include persistent dummy variables (Powell, Shi, Smith and Whaley (2006)) or signals from technical trading rules (Shintani, Yabu and Nagakura (2008)).

with current or future values of the regressors.[2] Since the predictive variables are predetermined, the ordinary least squares (OLS) estimators using correlated regressors are still consistent but biased in small samples. Mankiw and Shapiro (1986) demonstrate through Monte Carlo simulations that the bias may overstate the significance level of test statistics by as much as five times its nominal value for a sample size of 100. Stambaugh (1999) derives an explicit bias formula when the lagged regressor follows a first-order autoregression and infers that the slope coefficient estimator inherits the finite sample bias in the sample autocorrelation of the regressors.[3]

Data mining distorts classical statistical inferences when researchers fail to consider the effective number of searches through a given data set. As noted by Denton (1985) and Foster et al. (1997), data mining can occur in "naïve" patterns; a group of independent investigators whose research is motivated by past work uses the same data and evaluates the model without accounting for the knowledge of other results. The issue may be more problematic and difficult to handle because of the fact that only 'significant' results are published and the number of insignificant tests performed is unknown.

While all of these problems are clearly relevant to stock return predictability, no previous study has investigated their interaction. When the effects interact, their practical impact can only be understood by studying them simultaneously. Spurious regression, data mining, and lagged stochastic regressor bias are likely to interact. Ferson et al. (2003) find that data mining and spurious regression interact and reinforce each other in that researchers are more likely to find the spurious, persistent predictors through the mining process. If there are some regressors correlated with the predictive regression disturbances, a similar argument suggests that researchers are likely to find these biased predictors. Thus, lagged stochastic regressor bias and data mining are also likely to interact.

Spurious regression is a problem with estimating standard errors when the underlying expected

[2] A widely known regressor is the dividend-price ratio whose innovations at time $t+1$ is likely to be negatively correlated with the regression residuals at time $t+1$, because the price enters into the ratio's denominator.

[3] Amihud and Hurvich (2004) propose a procedure to estimate Stambaugh (1999)'s bias formula with a correct standard error estimator. Subsequent research by Amihud, Hurvich and Wang (2008) proposes a hypothesis testing procedure with the reduced-bias estimator. Alternative test procedures have been proposed by financial econometricians using nearly-integrated process models when the predictor's autocorrelation parameter is close to one. Such an asymptotic framework has been studied by Elliott and Stock (1994), Cavanagh, Elliott and Stock (1995), Perron and Vodounou (2004) and many others. Campbell and Yogo (2006) propose a pretest to determine whether to use the conventional t-test or the local-to-unity asymptotics.

return is highly persistent over time.[4] Like spurious regression, lagged stochastic regressor bias affects the inference if the predictor is highly autocorrelated. However, this bias primarily affects the coefficient estimator, and can arise even when the underlying expected return is not predictable over time. Lagged stochastic regressor bias disappears as the sample size increases, while the spurious regression effect persists.

Spurious regression and lagged stochastic regressor bias either reinforce or offset each other. In a one-sided test of the null hypothesis that the true coefficient is zero, the lagged regressor bias will reinforce the spurious regression effect if it shifts the distribution of the coefficient estimator in favor of the alternative hypothesis. The two biases, however, can offset when the distribution shifts in the opposite direction. The direction of the effect relies on the correlation between the regressor's autoregressive innovations and unexpected returns, with its magnitudes depending on the sample size.

A set of potential predictive variables is unobservable and likely to increase as more information accumulates. If a mining had occurred by testing a series of regression models, a variable incurring the reinforcing effects of two biases would have had more probabilities to appear as significant than a variable with the offsetting effects, irrespective of their true predictability. In this paper 386 macroeconomic and accounting variables from 23 countries are collected to provide the sampling properties for generating a set of potential predictive variables. The summary statistics suggest that highly persistent variables are likely to be negatively correlated with unexpected returns, which indicates presence of the reinforcing effects between spurious regression and the positive lagged regressor bias. Therefore, if this data set is subject to mining, these variables are at much better odds of finding significant.

This paper also presents a generaliztion of Stambaugh's (1999) bias adjustment that accounts for the unobservability of the "true" expected return. The theoretical bias expression tells us that the time-varying expected return may contribute to the lagged regressor bias if its autocorrelation differs from that of the measured regressor. I simulate the expectation of the lagged regressor bias

[4] Spurious regression in return prediction occurs since the regression errors inherits the autocorrelation from underlying expected returns when the predictor is independent. As the predictor becomes correlated with the expected return and captures its autocorrelations, the spurious regression effects diminishes with the less autocorrelated regression errors. There is no spurious regression when the predictor and the time-varying expected return is perfectly correlated, no matter how much persistent the predictor is.

associated with predictors that are imperfectly correlated with the true expected return and show how well the derived formula describes the finite-sample bias. I investigate the performance of two bias-correction methods that are currently available: the reduced-bias estimator by Amihud and Hurvich (2004) and a plug-in version of Stambaugh (1999)'s bias formula. The comparison illustrates that the former is preferable to the latter since it provides a consistent bias-correction with various degrees of the true expected return's autocorrelation. However, the pattern of remaining small sample bias after correction follows that of the original bias, possibly indicating a new bias term accompanied by imperfect predictors that cannot be corrected by the existent methods.

The empirical analysis is performed to re-evaluate the evidence of international return predictability. Adjusting for spurious regression and lagged stochastic regressor bias, I find that the evidence of the world market return predictability is vulnerable to data mining of 10 or more independent variables, only with exception of three predictors. In predicting national equity market returns I find that 8 of the 18 market returns may still have at least one significant predictive variable after we take into account of mining the global and local predictors.

The paper proceeds as follows. Section I presents the summary of previous studies and provides an empirical analysis on proposed predictor variables. Section II brings in the model for predictive regressions to provide an analysis of lagged stochastic regressor bias with unobservable expected returns. Section III presents the simulation designs for studying interactions of spurious regression, lagged stochastic regressor bias and data mining, and reports the simulation results. Section IV conducts a re-evaluation of the evidence for international stock return predictability. Section V provides concluding remarks.

I. The Data

Table I presents a list of predictors proposed in major studies investigating international equity return predictability. Various combinations of variables have been studied for the subperiods of 1956 through 2002 and most of the samples start from February 1970 or later with the stock market data obtained from the Morgan Stanley Capital International (MSCI).[5] The number of markets in

[5] Conover et al. (1999) use stock market data from the OECD's *Main Economic Indicators: Historical Statistics* and the IMF's *International Financial Statistics*. Their sample starts on January of 1956.

each study varies from four to twenty-one. In many cases, the predictive variables are divided into two categories: local and global (common) predictors. The global predictor set largely consists of U.S. variables that have been shown to possess explanatory power for U.S. stock returns. The local predictor set mostly consists of local counterparts to global predictors.

Table II provides summary statistics of the global predictors and their predictive regression results for the world market return. The return is calculated from the MSCI world index, which is a weighted average of developed market indices, and is measured in excess of the one-month U.S. Treasury bill return from the Center for Research in Security Prices (CRSP). Note that typical regressors are highly persistent with their autocorrelation estimates more than 0.9 for nine variables and above 0.95 for three variables, out of 16 predictors. The high serial correlations of the predictors strongly suggest that there may exist spurious regression and lagged stochastic regressor bias (e.g. Stambaugh (1999), Ferson et al. (2003)).

Table II reports the slope coefficient estimates and t-statistics using the OLS and reduced-bias t-statistics. The OLS t-statistic, t_{HAC}, is calculated using the Newey-West (1987) standard error estimator, where the number of lags for the Bartlett kernel is determined based on the data-dependent automatic bandwidth parameter estimators proposed by Andrews (1991).[6] The reduced-bias t-statistic, t_{AH}, is constructed following the procedure by Amihud and Hurvich (2004) to adjust for the lagged stochastic regressor bias. [7] The absolute values of the t_{HAC} are larger than 1.645 for ten predictors.[8] Eleven predictors have the absolute values of the t_{AH} larger than 1.645. For some

[6]In order to apply Andrews' (1991) method, we approximate as an AR(1) the autocorrelation process of the residuals for the long-run covariance matrix that are the cross-products of regressors and regression disturbances. Andrews (1991) recommends the number of lags for the bartlett kernel, m, to be determined as $m = 1.3221\,(\hat{\alpha}T)^{1/3}$, where $\hat{\alpha}$ estimates a function of the unknown spectral density matrix. For the $p \times p$ covariance matrix, he suggests to estimate $\hat{\alpha}$ as $\hat{\alpha} = \sum_{a=1}^{p} w_a \frac{4\hat{\gamma}_a^2\sigma_a^2}{(1-\hat{\gamma}_a)^6(1+\hat{\gamma}_a)^2} / \sum_{a=1}^{p} w_a \frac{\hat{\sigma}_a^4}{(1-\hat{\gamma}_a)^4}$ where γ_a and σ_a are the autoregressive and innovation variance parameters of the residuals and w_a denotes the weights that are set to zero for the intercept parameter and one for the others.

[7]If we correct the first-order bias of the slope coefficient estimator by simply plugging sample estimates into Stambaugh (1999)'s formula, its OLS standard error estimator may be biased by ignoring the sampling variability of the bias correction. Amihud and Hurvich (2004) propose the reduced-bias slope coefficient estimator that can be obtained by including the lagged regressor's autoregressive innovations in the regression model such that

$$r_{t+1} = \alpha + \delta z_t + \phi v_{t+1} + e_{t+1},$$

where v_{t+1} is the innovations of the regressor z_t at $t+1$. The formal procedures are summarized in Amihud and Hurvich (2004) and Amihud, Hurvich and Wang (2008).

[8]It can be regarded as performing the one-sided tests with 5 percent significance level with its alternative hypothesis corresponding to the sign of estimated slope coefficient. Thus, we assume the researcher has a prior belief about the relation of the variable to expected returns.

predictors, the absolute bias-corrected t-ratios decrease more than half compared with the t_{HAC} but they still indicate significance at standard levels. The last three columns report the adjusted R-squares, the sample correlations between the regression residuals and the predictor's autoregressive innovations, and the number of lags used to calculate the Newey-West standard error estimator. The R-squares are all less then seven percent and the sample correlations range from -0.74 to 0.20. If the correlation is positive, the lagged stochastic regressor bias is likely to be negative and vice versa. Altering signs of the correlations suggest that there might be different interactions among spurious regression, lagged stochastic regressor bias and data mining among these variables.

Table A.1 extends the empirical investigation of the global predictors' ability to predict eighteen national equity market returns.[9] The sample correlations, $Corr\,(u, v)$, which are the key determinants of lagged stochastic regressor bias, are more widely spread out in the regressions for the national equity market returns. For example, the U.S. market return is positively correlated to the lagged world market return with a correlation of 0.86, and negatively correlated to the lagged dividend yield on the S&P 500 with a correlation of -0.83. The same predictor may have different correlations from one country return to another. For example, the lagged *Bond Yield* has a correlation of 0.25 with the U.S. market return and -0.06 with the Hong Kong market return. These widely distributed, different correlations make international markets a good setting to study the interactions of the various statistical biases. They also suggest that understanding the interactions is necessary for a reliable evaluation of the true predictability.

Lagged stochastic regressor bias appears to have limited influence on classical inferences unless spurious regression and data mining are taken into account. Among 288 univariate regressions, 114 t-ratios are larger than 1.645 in absolute value before correcting for the lagged regressor bias. After adjusted for the first-order bias, three of these decrease to less than 1.645 while nine of the previously insignificant t-ratios become significant. When we increase the critical value to 1.96, 93 t-ratios and 98 bias-adjusted t-ratios are larger than the critical value. Correction for the lagged stochastic regressor bias alone hardly changes the usual significance results in the international return predictability literature.

In order to incorporate data mining, I construct a data set involving the global and local

[9] As of June 2007, the MSCI World Index consists of the twenty three developed market country indices. We examine eighteen indices whose historical returns are available from February, 1970.

predictors examined in the studies of Table I and generate a set of potential regressors using the sampling properties taken from these series. First, eighteen lagged variables, including valuation ratios and macroeconomic variables, are constructed for each of twenty three countries whose stock prices are weighted to calculate the world market index. The total number of variables is 386 and the details are provided in Appendix C. In the simulations, these series are permanently ordered according to the randomly generated numbers between 1 and 386. When the analyst mines the data set, for example, with 100 series, the sampling properties of the first 100 series are used to calibrate the parameters in the simulations.

Table III summarizes the sampling properties of the potential predictors.[10] Panel 1 provides the summary statistics of the autocorrelation parameters and the sample correlations between the regressor's autoregressive residuals and the world market return. When the predictable component is small in stock returns, these correlations proxy for the correlations between unexpected return and the regressor's disturbances (Pastor and Stambaugh, 2008). The number of regressors with highly positive correlations (≥ 0.5) are almost the same as the number of regressors with highly negative correlations (≤ -0.5), with each representing about 5 and 6 percent of the samples. Panel 2 provides a two-way sort of the predictors according to γ and ρ_{uv}, where γ is the autocorrelation parameter of the lagged predictor and ρ_{uv} is the correlation between the unexpected return and the regressor's disturbances. More than half of the series are highly persistent with autocorrelation parameter estimates greater than or equal to 0.9.[11] Among the regressors highly correlated with unexpected returns, the negatively correlated ones tend to be highly persistent whereas the positively correlated ones are not persistent. As discussed below, lagged stochastic regressor bias is stronger in highly persistent regressors while the negative correlation implies that the slope coefficient estimate is biased toward positive values. The highly persistent regressors are also likely to be affected by spurious regression problems if the time-varying expected returns are persistent. Therefore, if the researchers have mined the data set, the data mining effects are likely to be confounded with spurious regression and positive lagged stochastic regressor bias.

[10] The lagged world market return is excluded in Table III because its correlation with the stock return is one.

[11] These sample autocorrelations are corrected for the first-order bias as $\hat{\rho} + \frac{1+3\hat{\rho}}{T}$ to calibrate the true autocorrelations for generating a set of predictors. However, Lewellen (2004) points out that correcting the bias with the usual unconditional expression may produce over-corrected estimates when $\hat{\rho} - 1$ (the minimum value of $\hat{\rho} - \rho$) is greater than $E[\hat{\rho} - \rho]$, i.e. $\hat{\rho}$ is close to one, given that ρ is assumed to be strictly less than one. We do not correct the first-order bias for the estimates when $\hat{\rho} - 1 \geq E[\hat{\rho} - \rho]$, or $\hat{\rho} \geq \frac{1+T}{T-3}$.

II. The Models

Consider decomposing the stock return, r_{t+1}, into an expected return, $E_t[r_{t+1}]$, conditional on an unobserved "market" information set at time t and an unpredictable shock, u_{t+1}. An analyst observes a lagged variable, Z_t, that he believes belongs to the market information set and wants to test whether Z_t predicts the next period stock return r_{t+1} by running a time-series regression

$$r_{t+1} = \alpha + \delta Z_t + e_{t+1}. \tag{1}$$

while the true data-generating processes are

$$r_{t+1} = E[r] + \mu_t + u_{t+1}, \tag{2}$$

$$\mu_{t+1} = \rho\mu_t + w_{t+1}, \tag{3}$$

$$Z_{t+1} = \gamma Z_t + v_{t+1}, \tag{4}$$

where μ_t is regarded as the deviations of the conditional mean from the unconditional mean of the stock return, $E[r]$, so that $E_t[r_{t+1}] = E[r] + \mu_t$. It is assumed that μ_t and Z_t are stationary so that the autoregressive parameters ρ and γ are strictly less than one.[12] The residual vector $(u_t, v_t, w_t)'$ is assumed to be independently and identically distributed over time t with zero mean and covariance matrix Σ. Pastor and Stambaugh (2008) call a version of this data-generating process a "predictive system".

The data-generating system (2)-(4) implies that the true value of δ in the regression model (1) would not be zero if the stock return were predicted by Z_t. The predictability in returns can be captured by the "*true-*R^2", obtained from regressing r_{t+1} on μ_t, as if μ_t were observed. Provided that the expected return is predictable, a given instrument Z_t may or may not be a valid predictor. This can be captured by the "*true-validity*" of Z_t, defined as the conditional correlation between μ_t and Z_t, ρ_{vw}.[13]

[12] Ai (2005) derives the asymptotic distributions for spurious regression problem by modeling μ_t and Z_t as nearly integrated processes, based on Nabeya and Perron's (1994) asymptotic theory for nearly integrated ARMA(1,1) processes. This paper assumes stationary μ_t and Z_t to allow data mining to occur in a set of variables with the various degrees of autocorrelation.

[13] The i.i.d. assumption for v_t and w_t implies that the conditional correlation between μ_{t+1} and Z_{t+1} is equivalent to the unconditional correlation between w_{t+1} and v_{t+1}, ρ_{vw}.

The slope coefficient δ in the regression model (1) captures the comovement between time-varying expected returns and the lagged regressor, and thus, depends on the structural parameters in the system (2)-(4). The true regression coefficient, δ_0, in the regression model (1) is defined as $\delta_0 \equiv Cov\left(\mu_t, Z_t\right)/Var\left(Z_t\right) = \rho_{vw}\frac{\sigma_w}{\sigma_v}\left(\frac{1-\gamma^2}{1-\rho\gamma}\right) = \rho_{vw}\frac{\sigma_u}{\sigma_v}\left(\frac{1-\gamma^2}{1-\rho\gamma}\right)\sqrt{\frac{(1-\rho^2)true\text{-}R^2}{1-true\text{-}R^2}}$, which shows that δ_0 is zero when either the *true-validity*, ρ_{vw}, or the *true-*R^2 is zero.[14]

A. Lagged Stochastic Regressor Bias with Imperfect Predictors

A.1. Theoretical Analysis

The extant literature analyzes the lagged stochastic regressor bias under the assumption that the true return generating processes follow the model (1) and (4), implying the predictor Z_t is perfectly correlated with the true expected return (e.g. Stambaugh, 1999; Amihud and Hurvich, 2004; Perron and Vodounou, 2004; Campbell and Yogo, 2006).[15] In that case, the regression residual, e_{t+1}, becomes equivalent to the unexpected return, u_{t+1}, and there is a finite sample bias in the slope coefficient estimator because u_{t+1} is correlated with the current or future values of Z_{t+1}. Stambaugh (1986, 1999) shows that the finite-sample bias can be approximated to order of T^{-1} as $E\left[\hat{\delta}-\delta_0\right] = \frac{\sigma_{uv}}{\sigma_v^2}\left(-\frac{1+3\gamma}{T}\right) + o\left(T^{-1}\right)$.

However, the evidence of weak predictability in the stock returns suggests that most of the possible predictors are, at best, weakly correlated with μ_t, i.e. μ_t is not in an exact linear relation with Z_t as noted by Pastor and Stambaugh (2008). In the subsequent analysis, I follow their terminology to call Z_t as an "imperfect predictor" when μ_t can be only partially captured by Z_t. Applying Edgeworth approximations to the OLS estimator of $\hat{\delta}_0$ in Appendix A, the lagged stochastic regressor bias in the slope coefficient estimator can be approximated to order T^{-1} for the imperfect predictor as:

$$Bias \equiv E\left[\hat{\delta}-\delta_0\right] = -\delta_0\frac{1}{T}\frac{(\rho-\gamma)\left(1-\rho\gamma^2+3\gamma(1-\rho)\right)}{(1-\rho\gamma)\left(1-\gamma^2\right)(1-\rho)} - \frac{\sigma_{uv}}{\sigma_v^2}\left(\frac{1+3\gamma}{T}\right) + o\left(T^{-1}\right), \quad (5)$$

[14] The stationarity assumption allows us to write μ_t and Z_t as an infinite sum of innovations, $\mu_t = \sum_{i=0}^{\infty}\rho^i w_{t-i}$ and $Z_t = \sum_{i=0}^{\infty}\gamma^i v_{t-i}$. Then, $\delta = Cov\left(\mu, Z\right)/Var\left(Z\right) = \sum_{i=0}^{\infty}\left(\rho\gamma\right)^i\sigma_{vw}/\sum_{i=0}^{\infty}\gamma^{2i}\sigma_v^2 = \frac{\sigma_{vw}}{\sigma_v^2}\left(\frac{1-\gamma^2}{1-\rho\gamma}\right)$. Further, $\sigma_u^2 = Var\left(r_{t+1}\right)\left(1-true\text{-}R^2\right)$ and $\sigma_w^2 = \left(1-\rho^2\right)Var\left(\mu\right) = \left(1-\rho^2\right)\left(Var\left(r_{t+1}\right)-\sigma_u^2\right) = \sigma_u^2\left(1-\rho^2\right)\left(true\text{-}R^2/\left(1-true\text{-}R^2\right)\right)$.

[15] It is equivalent to make an additional assumption in our model that there exists an exact linear relation between μ_t and Z_t, and thus between w_t and v_t.

where the true regression coefficient is $\delta_0 = \frac{\sigma_{vw}}{\sigma_v^2}\left(\frac{1-\gamma^2}{1-\rho\gamma}\right)$.[16] The formula (5) reduces to Stambaugh's (1999) formula when the autocorrelation parameter of the expected return, ρ, coincides with the regressor's parameter, γ, or when there is no predictability with $\rho_{vw} = 0$ or *true*-$R^2 = 0$.

Suppose that Z_t is imperfectly correlated with μ_t and follows a different AR process. If μ_t were observable, we would regress it against Z_t and obtain the regression errors of $\eta_t \equiv \mu_t - \delta_0 Z_t$. Since ρ is different from γ, the expectation of regression errors η_t conditional on $Z = (Z_1, \ldots, Z_T)'$ is not zero as η_t is correlated with past values of the regressor.[17] Thus, the regression errors in the model (1), $e_{t+1} = \eta_t + u_{t+1}$, are not only correlated with the current or future values of regressors $(v_{t+1}, v_{t+2}, \ldots)$, as in Stambaugh (1999), but also correlated with the past values of regressors.

A.2. Evaluating the Bias Formula

The fact that the bias formula (5) is very nonlinear with various structural parameters ρ, γ and Σ entails a great difficulty in its evaluation. Nevertheless, it is suggested that the sign of the first term is crucial for its effects because it can offset or reinforce the Stambaugh's bias formula derived with a perfect predictor. The sign is first determined by Z_t's true-validity, ρ_{vw}, and by whether ρ is greater or less than γ.

Figure 1 plots $T \times Bias$ using the formula (5) against ρ for various values of γ and ρ_{vw}. I examine four values of γ that are greater than or equal to 0.9 and two different *true-validity*, 0.5 and -0.5, whereas the *true*-R^2 is set equal to 0.15 and $\sigma_v = \sigma_w$. I set $\rho_{uv} = -0.5$ in order that the perfectly-correlated regressor's bias term should be positive. When the *true-validity* is positive and $\rho < \gamma$, the first bias term is positive and reinforces the second. The first graph illustrates that the total bias, adjusted for the number of observations, is about 6.0 with zero autocorrelation for μ_t and increase as long as $\rho < \gamma$. However, once ρ becomes greater than γ, the two bias terms offset each other and the total bias starts to fall sharply.

Interactions occur to the opposite direction with a negative *true-validity.* The second graph illustrates that the total bias is about 2.7 with $\rho_{vw} = -0.5$ and not very different across various values of γ as ρ increases but $\rho < \gamma$. But once $\rho > \gamma$, the two terms reinforce each other and the

[16] The bias derivation is based on the assumption of normal residual vectors in the system (2)-(4) to expedite the fourth-order moment calculations. Appendix A provides the details.

[17] For example, when $k \geq 1$, $Cov(\eta_t, Z_{t-k}) = \rho^k Cov(\mu_{t-k}, Z_{t-k}) - \delta_0 \gamma^k Var(Z_{t-k}) = (\rho^k - \gamma^k) Cov(\mu_{t-k}, Z_{t-k}) \neq 0$ if $\rho \neq \gamma$.

graphs of total bias for all highly persistent γ's show an abrupt increase in the magnitude.

To examine the performance of this formula, I conduct Monte Carlo simulations of the predictive system (2) to (4) with the parameter values as given above. The sample mean and variance of the MSCI world market return is used to generate the stock return series, r_{t+1}, of length $T = 100$ and $\hat{\alpha}$, $\hat{\delta}$ in regression model (1) are estimated from 10,000 simulation trials. Figure 2 plots $T \times E[\hat{\delta}_{OLS} - \delta_0]$, where the expectation is evaluated with averages of $\hat{\delta}_{OLS}$ over 10,000 replications. To draw the graphs, $T \times E[\hat{\delta}_{OLS} - \delta_0]$ are evaluated for the interval of 0.01 for the values of ρ, starting from 0.01 to 0.99. Compared with Figure 1, the Monte Carlo estimates of bias display little discrepancies with the predicted bias using formula (5), except for the range of very high autocorrelations (e.g. $\rho, \gamma = 0.99$) where the stationarity assumptions are not likely to hold any more.

A.3. Bias Corrections for Imperfect Predictors

Implementing the bias estimation using formula (5) can face difficulties because the formula requires knowledge of the true values of δ_0, ρ_{uv} and ρ. In particular, it is likely to be tampered with estimating ρ of the underlying expected return. In order to estimate it, we would write the return process as an ARMA(1,1) which arises from combining the systematic equations (2) and (3) such that

$$r_{t+1} = \rho r_t + \varepsilon_{t+1} - \theta \varepsilon_t,$$

where ε_t is a white noise process. The exposition in Appendix B impose a moment condition on the MA coefficient θ that is governed by ρ, ρ_{uw} and *true*-R^2. If we account for a weak predictability with small *true*-R^2 or a highly persistent expected return, θ is close to ρ and the estimates of ARMA(1,1) parameters are likely to be inconsistent because the process becomes a nearly-white noise process (Nabeya and Perron (1994), Robertson and Wright (2009)). If $\rho = \theta$, $(1 - \rho L)\, r_{t+1} = (1 - \rho L)\, \varepsilon_{t+1}$ and the return process simply becomes a white noise process.

Here, I examine the performance of two different bias-corrected estimators that are currently available: a plug-in version of Stambaugh (1986)'s bias formula and the reduced-bias estimator proposed by Amihud and Hurvich (2004)[18]. Figure 3 and 4 plot $T \times E[\hat{\delta}_i - \delta_0]$ against ρ with the

[18] For the plug-in version of bias-corrected estimator, I first estimate the regressor's autocorrelation parameter and the innovations, adjusted for the second-order bias such that $\hat{\gamma}_b = \hat{\gamma} + (1+3\hat{\gamma})/T$ and estimate $\hat{e}_{t+1}$ from the regression

other parameter values given in the previous experiments, where $i = OLS$ for an OLS estimator, $i = plug$ for a plug-in estimator, and $i = AH$ for the reduced-bias estimator. Figure 3 presents that when $\rho_{vw} = 0.5$ the reduced-bias estimator dominates the plug-in correction for most of the return's AR parameter values. When the predictor is highly persistent with $\gamma \geq 0.97$, the plug-in correction happens to perform better but it soon deteriorates with ρ increasing. The performance of the reduced-bias estimator is quite consistent with adjusting more than half of the finite-sample bias in the OLS estimator, even when ρ is quite persistent. However, it is observed that, as $\rho \geq \gamma$, the offsetting effects become manifest to affect the performance of bias corrections. It may be that the remaining finite sample bias is due to the first term in formula (5), which prevents the reduced-bias estimator from a full correction.

Figure 4 illustrates the finite-sample bias properties with $\rho_{vw} = -0.5$. Again, the reduced-bias estimator consistently corrects the finite-sample bias except for the extremely highly persistent predictors. However, there occurs an over-correction with the estimator so that the estimates are biased to the slightly negative values in averages. In particular, when $\rho \geq \gamma$ and the two terms in formula (5) reinforce each other, the average bias estimates adjusted with the reduced-bias estimator hike up to the very large positive values like those of the original OLS bias. Thus, these observations seem to suggest another evidence that the first term in formula (5) affects the reduced-bias estimator and it is not corrected by the latter.

This section concludes that the reduced-bias estimator proposed by Amihud and Hurvich (2004) should be preferred to a plug-in version of bias correction when the regression model involves an imperfect predictor. It should, nonetheless, be aware that the imperfectness of predictors (i.e. $|\rho_{vw}| \in (0, 1)$) can result in a finite-sample bias, which cannot be corrected by the reduced-bias estimator and interacts with the small-sample bias pointed out by Mankiw and Shapiro (1986) and Stambaugh (1986).

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model (1) to estimate

$$\hat{\delta}_{plug-in} = \hat{\delta} + \frac{\hat{\sigma}_{ev}}{\hat{\sigma}_v^2}\left(\frac{1 + 3\hat{\gamma}_b}{T}\right).$$

III. Interactions of three problems in Predictive Regressions

A. Methodology

This paper turns the attention to the combined effects of spurious regression, lagged stochastic regressor bias and data mining on the statistical inferences, particularly when these problems affect the researchers to find a spurious predictor for the expected return. I address these concerns by considering the situation where all the variables in the potential set of predictors are independent from the true expected return.

The stock return predictability is governed by the two important parameters, *true-*R^2 and *true-validity,* as described above. Throughout the simulations, I set the *true-validity,* ρ_{vw}, equal to zero for each predictor to be independent and vary the *true-*R^2 over a range of values to consider the various degrees of return predictability.

A.1. Spurious Regression and Lagged Stochastic Regressor Bias

This study first investigates the effects of spurious regression and lagged stochastic regressor bias for testing an individual regression model without data mining concerns. Simulation experiments are conducted with randomly generated samples. First, residuals are drawn as a 3×1 normally distributed vector with mean zero and covariance matrix Σ. These residuals are used to construct the time series $(r_{t+1}, \mu_t, Z_t)'$ following the data-generating system (2)-(4), where the initial values of μ_t and Z_t are drawn from a normal distribution with mean zero and variances, $Var(\mu_t)$ and $Var(Z_t)$, and the first 100 observations are discarded to eliminate the effects of the initial values. $Var(\mu_t)$ is set equal to the sample variance of the MSCI world market return in excess of a one-month U.S. Treasury bill return, multiplied by the *true-*R^2, and the unconditional mean of the stock return, $E[r]$, is set equal to the sample mean. The variance of the measured regressor is essentially arbitrary, so it is set equal to $Var(\mu_t)$. In order to consider various degrees of return predictability, the *true-*R^2 varies between 0.1 and 15 percent.

Ferson et al. (2003) suggest that spurious regression occurs in a predictive regression when the standard error estimator fails to capture the autocorrelations in regression residuals and, as a result, the estimated standard errors are too small. Lagged stochastic regressor bias makes the slope coefficient estimator biased, either positively or negatively. To illustrate interactions of the different effects, this paper will focus on testing the one-sided alternative hypothesis that $\delta > 0$ against the null hypothesis of no predictability.

Spurious regression is likely to appear in the regression model (1) when both ρ and γ are large and with a non-zero *true-*R^2. The extent of the lagged stochastic regressor bias depends on the off-diagonal elements of Σ, along with the regressor's persistence parameter, γ. When Σ is set to be a diagonal covariance matrix, the parameter settings reduce to those in Ferson et al. (2003) and we observe only the spurious regression effect. In relaxing the diagonal covariance matrix assumption, however, we cannot vary freely all of the off-diagonal elements because Σ must be positive semi-definite. By applying the cholesky decomposition, the positive semi-definiteness of Σ obtains with the condition $(\rho_{vw} - \rho_{uv}\rho_{uw})^2 \leq (1 - \rho_{uv}^2)(1 - \rho_{uw}^2)$, as noted by Pastor and Stambaugh (2008).

According to the bias formula (5), lagged stochastic regressor bias will be affected primarily by the correlation ρ_{uv} especially when the lagged variable has no explanatory power for the expected return. The values of ρ_{uv} are likely to be reflected in the sample estimates of the correlation between stock returns and regressor's innovations, ρ_{rv}, given a small *true-*R^2.[19] I call ρ_{uv} the measured regressor's '*discount-rate effect'* correlation, as it determines the direction of lagged regressor bias and allow it to vary over a range of values based on the estimated correlations in Tables II and Appendix C.[20]

For our simulations it is assumed that the *true-validity*, ρ_{vw}, is zero.[21] In order to ensure that the true expected return is independent, I generate the expected return's residuals, w_t, independently from the other residuals, u_t and v_t, and set $\rho_{vw} = \rho_{uw} = 0$.[22] Regarding the autocorrelation

[19] Using the conditions of positive semi-definiteness, we have that $(\rho_{rv} - \rho_{uv}\rho_{ru})^2 \leq (1 - \rho_{uv}^2)(1 - \rho_{ru}^2)$. Then, $\rho_{rv} \approx \rho_{uv}$ given a small *true-*R^2 where $1 - \rho_{ru}^2 = $ *true-*R^2.

[20] The '*discount-rate effect*' is termed to refer to the negative correlation between shocks to expected returns and shocks to prices by Fama and French (1988). In this sense, the correlations between innovations of the expected return and unexpected returns, ρ_{uw}, can be regarded as the unobserved, full '*discount-rate effect correlation*'.

[21] If there exist the full *'discount-rate effects'*, ρ_{uw} will be negative. (Pastor and Stambaugh (2008)). The sample correlations of ρ_{uv} is likely to be close to -1 for most of the financial ratios that have prices in the denominator. If we believe ρ_{uw} is close -1 along with the *discount-rate effect correlation*, ρ_{uv}, close to -1, the regressor is likely to be a real predictor for the expected return as the *true-validity*, ρ_{vw}, gets close to one by the positive semi-definiteness.

[22] Pastor and Stambaugh (2008) note that the autocovariance of regression errors in the model (1) can be written as $Cov(e_t, e_{t+1}) = \rho Var(\mu_t|Z_t) + Cov(u_t, w_t - \delta v_t)$. The residual covariance implies that the spurious regression effects can be crucially affected by the negative ρ_{uw} because the first term may be offset by the second term in the presence of the negative ρ_{uw}. Given the zero *true-validity* and the *discount-rate effect correlations* ranging from -.9 to .9, I run the simulations with the lowest possible negative ρ_{uw} satisfying the positive semi-definiteness of Σ and find no significant differences from the reported results.

parameters, ρ and γ, they can be set independently from each other but the lagged stochastic regressor bias formula (5) indicates that the values have impact on the slope coefficient estimator only when the true slope coefficient is not zero. Under the null hypothesis of no predictability, ρ and γ are set equal to each other and vary between 0 and 0.99.

Test statistics are calculated with the autocorrelation-heteroskedasticity-consistent (HAC) standard error estimator proposed by Newey and West (1987). The number of lags for the HAC estimators are determined following Andrews (1991)'s data-dependent automatic lag selection methods.[23] Simulations are run under different sample sizes in order to study how the interactions between the two biases change in accordance with T.

A.2. Data Mining

To incorporate data mining with spurious regression and lagged stochastic regressor bias, consider a situation when the analyst searches through M explanatory variables to find the "best" predictor for the stock return. The analyst sifts through M univariate regression models (1), where M varies from 1 to 250, examines the t-statistics for the slope coefficients and chooses the "best" predictor, with the maximum t-statistic. This study considers the situation where all the regressors are independent from the expected returns.

The procedure to generate the M variables and the simulated stock returns is as follows. Generate u_t and w_t from an independent normal distribution with zero mean and variances, σ_u^2 and σ_w^2, for the given values of *true*-R^2 and ρ. For the potential predictors, the M-vector of γ is constructed with the sample autocorrelation estimates of the first M predictors in 386 potential predictors described in the data section. The correlations of their autoregressive innovations with unexpected returns are captured by an M-vector of ρ_{uv} that is constructed by random draws from a normal distribution with mean of 0.5 or -0.5.[24] The autoregressive residuals are generated as $v_t = \beta u_t + \varepsilon_t$, where $\beta = \rho_{uv}\frac{\sigma_v}{\sigma_u}$ and ε_t is a normal M-vector with zero mean and variance Ψ, where Ψ is estimated

[23] The exact procedure is described in Footnote 3. Newey and West (1994) propose an alternative, computationally convenient procedure that determines the number of lags as $m = 4\,(T/100)^{2/9}$. In many empirical studies, a number of sample autocorrelations are calculated and the cutoff values are chosen at the minimun lag length where no higher order autocorrelation is larger than two standard errors. The simulation results do not change significantly with either alternative lag selection method.

[24] The standard error is set to 0.25 to make 95 percent of drawn correlations fall within (-1,1) and the drawn values with absolute value larger than one are discarded.

from the sample of 386 potential instruments in Appendix B.[25] Finally, I construct the time series r_{t+1}, μ_t and Z_t according to the system (2)-(4).

B. Results

B.1. Spurious Regression and Lagged Stochastic Regressor Bias

Table V summarizes the results for the effects of spurious regression and lagged stochastic regressor bias, with no data mining. The table reports 95 percent cutoff values for a one-sided Newey-West t-ratio from the empirical distributions, calculated from 10,000 simulation trials. Panels 1 and 2 run the experiments with small and large sample sizes, $T = 148$ and $T = 972$.[26]

There are three experiments with different *true-*R^2 in each panel. When the *true-*R^2 is set to 0.1 percent, the stock return is essentially unpredictable even if the underlying expected return is observed. In subsequent subpanels, the *true-*R^2 is set to 5 percent based on average estimates for the coefficient of determination in the univariate predictive regressions, or a "large" value of 15 percent. The *discount-rate effect* correlation, ρ_{uv}, ranges from -0.9 to 0.9 over the columns of Table V, based on the extreme sample estimates of international stock return predictive regressions summarized in Appendix C. Different rows correspond to different values of ρ and γ, which are set equal to each other and varying from 0 to 0.99.[27]

The pure spurious regression effect is demonstrated by the columns in which the *discount-rate effect* correlation, ρ_{uv}, is set to zero, similar to Ferson et al. (2003). In Subpanel A, where the stock return is essentially unpredictable, there is no spurious regression even if the true expected return is highly persistent with ρ being 0.95 or above. As the *true-*R^2 increases to 15 percent, the empirical critical t-ratio for sample size $T = 148$ increases from 1.7 to 2.9 for $\gamma = 0.97$. As noted by Ferson et al. (2003), the spurious regression effect does not diminish with an increase in the sample size, and it is likely to be even worse when the autocorrelation parameter is extremely high ($\gamma = 0.99$).

Subpanel A also illustrates the lagged stochastic regressor bias, suppressing the spurious re-

[25] In order to make the variance of v_t correspond to the sample variance, the variance of ε_t is set equal to $\left(1-\rho_{uv}^2\right)\left(1-\gamma^2\right) Var\left(Z\right)$.

[26] The first sample size matches the smallest sample size in Table III. The large sample size is determined based on the availability of U.S. monthly stock return series in the CRSP database, as of December 2006.

[27] When ρ is small, it is confirmed by simulations that spurious regression is of no concern even if γ is very large.

gression effect by setting the *true*-R^2 to 0.1 percent. As the formula (5) indicates, the direction of lagged regressor bias is determined by the sign of ρ_{uv} when the regressor is independent from the expected return. When ρ_{uv} is negative, there is a positive bias in the slope coefficient estimator, and the empirical distribution of the t-ratios moves to the right. Subpanel A's first column shows that the critical t-ratio is larger for $\rho_{uv} = -0.9$ than for $\rho_{uv} = 0$ and that it increases in accordance with the regressor's autocorrelation parameter, γ. When ρ_{uv} is positive, the slope coefficient estimator is negatively biased and the t-ratio shifts to the left. As a result, the critical t-ratios in the last column for $\rho_{uv} = 0.9$ are smaller than the theoretical critical value, and their differences become more pronounced as γ gets larger.

As we move down to subpanel B and C in Panel 1 spurious regression interacts with lagged stochastic regressor bias. Spurious regression effects reinforce lagged stochastic regressor bias when $\rho_{uv} < 0$. For example, if $\rho_{uv} = -0.9$, the empirical critical t-ratio is 2.7 (*true*-$R^2 = 0.05$) or 3.3 (*true*-$R^2 = 0.15$) when $\rho = \gamma = 0.95$. However, when $\rho_{uv} > 0$, the lagged regressor bias offsets the spurious regression effects. If $\rho_{uv} = 0.9$ and *true*-$R^2 = 0.15$, the critical t-ratios are between 1.5 and 2.2 even when $\rho = \gamma = 0.99$.

These patterns can be understood by recalling the fact that lagged stochastic regressor bias primarily affects the numerator of t-ratios while spurious regression produces non-convergent standard errors in the denominator. When there is a negative correlation between regressor's innovations and unexpected returns, there is a positive bias in the slope coefficient estimator and the critical value, which was 2.8 under pure spurious regression, increases to 3.3 with $\rho_{uv} = -0.9$, $\gamma = 0.95$ and *true*-$R^2 = 0.15$. Thus, spurious regression and the positive lagged regressor bias reinforce each other and, as we saw in Table III, this is likely to be an empirically relevant scenario in that the more persistent predictors tend to have the negative ρ_{uv}. When the correlation is positive, there is a negative lagged regressor bias in the slope coefficient. But the standard error is biased upward by spurious regression so that the two effects offset and the critical t-ratio becomes 2.2 rather than 2.8 if $\rho_{uv} = 0.9$.

In large samples, lagged stochastic regressor bias interacts with spurious regression in a different way. Panel 2 shows the effects of two biases for samples of $T = 972$. In Subpanel A, critical t-ratios are still affected by lagged stochastic regressor bias but to a much lesser degree than for smaller sample sizes. Of course, the lagged stochastic regressor bias eventually disappears as the sample size tends to infinity. However, spurious regression gets worse in large samples, especially for the larger values of γ and *true-*R^2. As a result, spurious regression dominates the lagged regressor bias in large samples. The combined effects in Subpanel C are different from those in small sample sizes. For different ρ_{uv} values, the critical t-ratio varies from 2.5 to 2.8 with $\rho = \gamma = 0.95$ and from 4.6 to 5.2 with $\rho = \gamma = 0.99$.

B.2. Data Mining with Spurious Regression and Lagged Stochastic Regressor Bias

The interactions of spurious regression and lagged stochastic regressor bias with data mining are summarized in Table VI under the four categories: *Pure Mining, Spurious*, *Lagged Regressor Bias* and *Spurious and Lagged Regressor Bias.* Similar to Table V, the experiments are run for two different sample sizes, 148 and 972, with two *true-*R^2, 0.05 and 0.15. The rows in each subpanel refer to different numbers of potential regressors, with which the analyst searches for the "best" predictor producing the largest absolute t-statistic. The number of potential regressors ranges between 1 and 250.

In this experiment, the spurious regression effects are suppressed in the *Pure Mining* and *Lagged Regressor Bias* columns by setting the expected return's autocorrelation, ρ, equal to 0.15. Meanwhile, ρ is set to 0.95 in the *Spurious* and *Spurious and Lagged Regressor Bias* columns in order to effectuate spurious regression. With regard to the lagged stochastic regressor bias, I choose the *discount-rate effect* correlations, ρ_{uv}, to be normally distributed around 0.5 in the *Positive* ρ_{uv} column and around -0.5 in the *Negative* ρ_{uv} column.

When only one regressor is employed to predict stock returns, there is no concern about data mining and the inferences are subject to spurious regression and lagged stochastic regressor bias, as examined in the previous section. Moving down the *Pure Mining* column, the critical values increase as an analyst mines a larger number of regressors. When the underlying expected return is not highly persistent ($\rho = 0.15$) and the unexpected return is independent from regressors over all leads and lags ($\rho_{uv} = 0$), there is only a data mining problem as in Foster et al. (1997), and it is unaffected by the amount of variability in the true expected returns.[28]

[28] The pure mining effect is confirmed with comparing the accompanied R^2 critical values with the values in Foster et al. (1997), which are similar.

When the underlying expected return is highly persistent ($\rho = 0.95$), spurious regression interacts with data mining as in Ferson et al. (2003). In Panel 1, with *true-*R^2 = 0.05, the critical value increases from 1.7 to 2.3 with $M = 1$ and from 5.1 to 6.4 with $M = 250$, moving from the *Pure Mining* to the *Spurious* columns. With *true-*R^2 at 0.15, spurious regression effects are more pronounced as the critical value reaches 8.2 for $M = 250$.

The *Lagged Regressor Bias* columns show that data mining also interacts with lagged stochastic regressor bias. First, the bias "offsets" data mining if an analyst searches the potential predictors that are positively correlated with unexpected returns. The slope coefficient estimates in this case are likely to be biased downward. When $M = 1$, the critical value is 0.6, but when $M = 250$, the critical t-ratio is 3.7 with positive ρ_{uv}'s, while it is 5.1 in the *Pure Mining* column without the bias. In contrast, if the potential predictors are negatively correlated with unexpected returns, lagged stochastic regressor bias can magnify the data mining effects. As M increases from 1 to 250, the critical t-ratio increases from 2.3 to 7.1 with negative ρ_{uv}'s. These results imply that standard adjustments for the effects of data mining will be misleading when there is also the lagged stochastic regressor bias, as the correct adjustments will depend on the *discount-rate effect* correlations, ρ_{uv}, in the set of mined instruments.

Unlike spurious regression, different degrees of return predictability do not affect the extents to which the lagged stochastic regressor bias interacts with data mining. As the *true-*R^2 increases from 5 to 15 percent for $M = 250$, the critical t-ratios hardly change from 3.7 with positive ρ_{uv} or from 7.9 with negative ρ_{uv} whereas they increase from 6.4 to 8.2 in the *Spurious* column. So, at a higher *true-*R^2, the spurious regression effects dominate the lagged stochastic regressor bias.

Finally, the *Spurious and Lagged Regressor Bias* columns illustrate how all three problems interact with each other. In the positive ρ_{uv} column where the expected return is highly persistent and potential predictors are positively correlated with unexpected returns, we see the offsetting effects of spurious regression and lagged stochastic regressor bias. As the number of potential predictors increases, the critical t-ratios are closer to the values in the *Pure Mining* column than in the other cases. With *true-*R^2 at 0.15, the spurious regression effect becomes more pronounced as the critical t-ratio is 6.2 whereas it is 5.1 for the pure mining case. These results may suggest that if we happen to have a combination of the right parameters values, classical data mining corrections could lead to the right inferences even with both spurious regression and lagged stochastic regressor bias.

The negative ρ_{uv} column illustrates the interactions occurring in a way that all three problems reinforce each other and overstate the t-ratios. As M increases from 1 to 250, the t-ratio increases from 3.4 to 9.0 for the 5 percent *true-*R^2, and from 4.2 to 10.5 for the 15 percent *true-*R^2. These values are much larger than simple data mining corrections alone would suggest, or than the interaction between spurious regression and data mining alone would suggest. The values of empirical t-ratios seems to be extreme for their own sake, as it assumes the *discount-rate effect* correlations normally distributed around -0.5. However, the summary statistics in Table III suggest that it is the most likely scenario in the international data that spurious regression, lagged stochastic regressor bias and data mining interact to reinforce each other.

As the sample size grows to $T = 972$, the effects of lagged stochastic regressor bias are less pronounced because the bias is a finite sample property, and the test statistics are primarily influenced by spurious regression and data mining. The last two columns with all the interactions present that regardless of whether data mining occurs in the set of positively or negatively correlated regressors, the critical t-ratios are larger than those in the *Pure Mining* column when the sample size is $T = 972$, implying that the offsetting effects disappear as the sample size increases.

IV. A re-evaluation of the evidence for Predictability

Table VII re-evaluates the evidence on predicting international equity market returns. Panel 1 revisits the predictive results in Table II for the world market returns using global predictors and Panel 2 turns the focus to the predictability of the eighteen national equity market returns using both global and local predictors. In Panel 1, the 95 percentile empirical critical values are reported for the t-statistics, t_{HAC} and t_{AH}, with sample sizes, autocorrelations and *discount-rate effect* correlations given in Table II. Incorporating data mining, the last three columns report the simulation results similar to Foster et al. (1997) to see how many searches would have to be performed in a set of independent, unrelated predictors to find a t-statistic at least as large as the reported OLS t-stiatistic with the HAC standard errors. For this exercise, I consider three different sets of the potential predictors of which autoregressive innovations are generated with the following specifications. For the M column, I use the *discount-rate effect* correlations estimated from the data. For the M^- and M^+ columns, the correlations are normally distributed around means of -0.5 and 0.5, respectively. The true R-squares are set to 10 percent and the autocorrelation of the underlying expected return, ρ, is set equal to the predictor's autocorrelation, γ.

Panel 1 shows that 10 of the 16 global predictors are considered significant if the standard critical values are naively applied. Two of them would no longer be regarded as significant when we consider the effects of spurious regression and lagged stochastic regressor bias alone. Similar conclusions can be reached with the bias-adjusted t-statistics. However, if we consider the problems combined with data mining, the critical values of M are less than 10 for most of the predictors, with only three exceptions.

Panel 2 examines individual national market return predictability using all the global and country-specific variables. The total number of regressions for each return is 30 or so, except for the Hong Kong market return whose country-specific variables are not available. Using the traditional measure of significance for t-statistics, there are roughly a third of predictors that are significant. Once spurious regression and lagged stochastic regressor bias are accounted for, the number of significant predictors is reduced by about half.

Finally, suppose that the researcher is a sophisticated miner willing to take into account the number of searches and wonders if the national market return is predictable with at least one lagged variable. He would investigate all the global and local predictors for the given market returns and test whether the predictor associated with the largest t-staitistic would be valid or not. The 'Largest t' column reports the largest t-statistic in absolute value from all the univariate regressions of each national equity market return. These values can be regarded as the maximum t-statistics obtained after performing the number of searches as many as in the second column. Thus, the number in the second column can be compared with the critical value reported in the M columns. For example, if he finds that the former is larger than the latter, he may conjecture that the reported t-statistic might have been obtained with fewer number of mining in a set of independent lagged variables and cannot reject the hypothesis that the predictability is an outcome of data mining. Using the data-dependent *discount-rate effect* correlations, there are eight national market returns for which we can reject the null hypothesis and there may exist at least one significant predictive regression model.

To compare with the values in M^- and M^+ columns, the sign of the reported t-statistic should be paid attention to. If it corresponds to the sign of *discount-rate effect* correlations the lagged stochastic regressor bias has an offsetting effect for spurious regression and data mining whereas the former reinforces the latter problems in the other case. If there happens the worst scenario where the potential predictor set is affected by only reinforcing effects, there remains only one national equity market, Canada, which has the larger critical value of M than the number of searches. In the best scenario where offsetting effects are dominating, eleven national equity market returns may have at least one significant predictor.

When the predictor is not highly autocorrelated and has a small *discount-rate effect* correlation, the predictive regression is less likely to be affected by spurious regression or lagged stochastic regressor bias. Panel 2 shows that the regression models producing the most significant t-statistics for the returns of Canada, Singapore, Sweden, and the U.K. have the predictive variable with an autocorrelation around 0.2 and a *discount-rate effect* correlation less than or equal to 0.11 in absolute value. For these markets, we may be less concerned about whether the predictive results are affected by the interactions of spurious regression, lagged stochastic regressor bias and data mining.

V. Conclusions

This article investigates the statistical properties of regression models that employ lagged variables to predict future returns in national equity markets. The evidence of international market return predictability is re-evaluated focusing on the issues of spurious regression, lagged stochastic regressor bias, and data mining. Simulation evidence reveals that the three problems, when considered simultaneously, interact with each other to have interesting implications for the predictive regressions. One problem might be reinforced or offset by the others.

Spurious regression is not a concern when the expected risk premium is not time-varying, even if the lagged regressor is highly persistent. The problem arises when the expected return is predictable and gets worse as it is more highly autocorrelated and predictable. As the predictive models are examined for different lagged variables with various degrees of autocorrelation, the highly persistent predictors have better odds of being found significant regardless of their true correlations with the underlying expected return.

Lagged stochastic regressor bias affects the slope coefficient estimator through *discount-rate effect* correlation. A substantial literature has paid attention to this bias and proposed various approaches to deal with the problem, particularly when the regression involves valuation ratios. When the lagged predictor is a ratio with stock price in the denominator, the correlations that determine the bias are likely to be negative and the bias in the regression coefficient estimator is positive.

As empirical evidence accumulates, a wide spectrum of predictive variables arises over macroeconomic variables, industrial measures, and the linear and nonlinear tranformations of these variables. When these variables are regressed against different national equity market returns, the *discount-rate effect* correlations are likely to spread over positive and negative values with creating diverse effects of lagged stochastic regressor bias. This survey observes this pattern for the international equity market return predictors examined in past studies, but finds that the positive bias is more likely to have an influence on the statistical inferences as more highly autocorrelated regressors tend to accompany the negative *discount-rate effect* correlations.

This paper runs simulations to study the interactions of spurious regression, lagged stochastic regressor bias and data mining. When all three problems reinforce each other, the actual critical t-ratios are overstated to the extent that the effects are much larger than simple data mining corrections alone would suggest or than the interaction between spurious regression and data mining alone would suggest. When lagged stochastic regressor bias offsets spurious regression and data mining, it can occur to the extent which the actual critical t-ratios get close to the values that would be suggested by classical data mining corrections such as Foster et. al (1997), depending on the underlying parameter values.

This paper revisits the evidence of international market return predictability. If we naively apply the usual critical values for the t-statistics, 10 of the 16 global predictors are considered significant for the world market return. However, the results are vulnerable to data mining of 10 or more independent variables when we account for the effects of spurious regression and lagged stochastic regressor bias, only with exception of three predictors. With regards to predicting national equity market returns using the global and local predictors, I find that 8 of the 18 national market returns may have at least one significant predictor after taking into account the interactions of three problems.

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Appendix

A Derivation of the Bias Approximation

In the following bias derivation, I assume that the residual vector $(u_t, v_t, w_t)'$ is normally distributed and independent across all the leads and lags. Let $R = (r_1, \ldots, r_T)'$, $\mu = (\mu_1, \ldots, \mu_T)'$, $Z = (Z_1, \ldots, Z_T)'$, and the lagged vectors of μ and Z be denoted by μ_{-1} and Z_{-1}. Define $F = \left(1, \gamma, \ldots, \gamma^{T-1}\right)'$, $G = \left(1, \rho, \ldots, \rho^{T-1}\right)'$, and the $T \times T$ matrices C, D as

$$C = \begin{bmatrix} 0 & 0 & 0 & & \cdots & 0 \\ 1 & 0 & 0 & & & \\ \gamma & 1 & 0 & & & \vdots \\ \gamma^2 & \gamma & 1 & \ddots & & \\ \vdots & & & \ddots & & \\ \gamma^{T-2} & & \cdots & \gamma & 1 & 0 \end{bmatrix}, \quad \text{and} \quad D = \begin{bmatrix} 0 & 0 & 0 & & \cdots & 0 \\ 1 & 0 & 0 & & & \\ \rho & 1 & 0 & & & \vdots \\ \rho^2 & \rho & 1 & \ddots & & \\ \vdots & & & \ddots & & \\ \rho^{T-2} & & \cdots & \rho & 1 & 0 \end{bmatrix}.$$

If it is assumed that the initial values of Z_0 and μ_0 are zero, we can simplify the expressions for the lagged vectors of μ and Z by $Z_{-1} = Z_0 F + Cv = Cv$ and $\mu_{-1} = \mu_0 G + Dw = Dw$ where $v = (v_1, \ldots, v_T)'$ and $w = (w_1, \ldots, w_T)'$. Define $\eta_{-1} = \left(\eta_0, \ldots \eta_{T-1}\right)'$ where $\eta_t = \mu_t - \delta_0 Z_t$. The bias of OLS estimator for the slope coefficient δ in the regression model (1) can be written as

$$\begin{aligned} E\left[\hat{\delta} - \delta_0\right] &= E\left[\left(Z_{-1}' M Z_{-1}\right)^{-1}\left(Z_{-1}' M \eta_{-1}\right)\right] + E\left[\left(Z_{-1}' M Z_{-1}\right)^{-1}\left(Z_{-1}' M u\right)\right] \\ &= E\left[N_1/D\right] + E\left[N_2/D\right], \end{aligned} \tag{A.1}$$

where $\delta_0 = \frac{\sigma_{vw}\left(1-\gamma^2\right)}{\sigma_v^2 (1-\rho\gamma)}$, $M = I - \frac{1}{T}\mathbf{1}\mathbf{1}'$, and $\mathbf{1}$ is a $T \times 1$ vector of ones. For each nominator and denominator in $(A.1)$, I can calculate its expectation as

$$\bar{N}_1 = E\left[N_1\right] = \sigma_{vw} tr\left(C'MD\right) - \delta_0 \sigma_v^2 tr\left(C'MC\right), \tag{A.2}$$

$$\bar{N}_2 = E\left[N_2\right] = \sigma_{uv} tr\left(MC\right), \tag{A.3}$$

$$\bar{D} = E\left[D\right] = \sigma_v^2 tr\left(C'MC\right). \tag{A.4}$$

To approximate the bias of $\hat{\delta}$ to order $O\left(T^{-1}\right)$, I expand D^{-1} around $\bar{D}^{-1}$ as in Grubb and Symons (1987)

$$\begin{aligned} E\left[N_i/D\right] &= E\left[N_i\right]\bar{D}^{-1} - E\left[N_i\left(D-\bar{D}\right)\right]\bar{D}^{-2} + o\left(T^{-1}\right) \\ &= \bar{N}_i/\bar{D} - Cov\left(N_i, D\right)/\bar{D}^2 + o\left(T^{-1}\right), \quad i = 1, 2 \end{aligned} \tag{A.5}$$

where the higher terms consisting of a series of following terms,

$$E\left[N\left[-\left(D-\bar{D}\right)\bar{D}^{-1}\right]^j\right]\bar{D}^{-1}, \quad j = 2, 3, \ldots$$

are of smaller orders than T^{-1} since $\bar{D}^{-1}N$ and $\left(D-\bar{D}\right)/\bar{D}$ both have order in probability $O_p\left(T^{-1/2}\right)$, as noted by Grubb and Symons (1987). In order to evaluate the eq. $(A.4)$ for $i = 1, 2$, we have that $Cov\left(N_i, D\right) = E\left[N_i D\right] - \bar{N}_i\bar{D}$ where

$$\begin{aligned} E\left[N_1 D\right] &= E\left[Z_{-1}'MZ_{-1}Z_{-1}'M\mu_{-1}\right] - \delta_0 E\left[Z_{-1}'MZ_{-1}Z_{-1}'MZ_{-1}\right] \\ &= \sigma_v^2\sigma_{vw}\left[tr\left(C'MC\right)tr\left(C'MD\right) + 2tr\left(C'MCC'MD\right)\right] \\ &\quad -\delta_0\sigma_v^4\left[tr\left(C'MC\right)^2 + 2tr\left(C'MCC'MC\right)\right], \end{aligned} \tag{A.6}$$

$$\begin{aligned} E\left[N_2 D\right] &= E\left[Z_{-1}'MZ_{-1}Z_{-1}'Mu\right] \\ &= \sigma_v^2\sigma_{uv}\left[tr\left(C'MC\right)tr\left(MC\right) + 2tr\left(C'MCMC\right)\right]. \end{aligned} \tag{A.7}$$

From the identities

$$\begin{aligned} CC' &= \left(1-\gamma^2\right)^{-1}\left(I + \gamma C + \gamma C' - FF'\right), \\ DC' &= \left(1-\rho\gamma\right)^{-1}\left(I + \rho D + \gamma C' - FG'\right), \end{aligned}$$

we can calculate the terms in trace as

$$\begin{aligned}
tr(MC) &= tr(C) - \frac{1}{T} tr\left(\mathbf{11}'C\right) = -(1-\gamma)^{-1} + O\left(T^{-1}\right) \\
tr\left(C'MC\right) &= tr\left(CC'\right) - \frac{1}{T} tr\left(C'\mathbf{11}'C\right) = \left(1-\gamma^2\right)^{-1} T - (1-\gamma)^{-2} + O\left(T^{-1}\right), \\
tr\left(C'MD\right) &= tr\left(DC'\right) - \frac{1}{T} tr\left(C'\mathbf{11}'D\right) = (1-\rho\gamma)^{-1} T - (1-\gamma)^{-1}(1-\rho)^{-1} + O\left(T^{-1}\right), \\
tr\left(C'MCMC\right) &= \left(1-\gamma^2\right)^{-2} \gamma T + O(1), \\
tr\left(C'MCC'MC\right) &= \left(1-\gamma^2\right)^{-3}\left(1+\gamma^2\right) T + O(1), \\
tr\left(C'MCC'MD\right) &= \left(1-\rho\gamma^3\right)(1-\rho\gamma)^{-2}\left(1-\gamma^2\right)^{-2} T + O(1).
\end{aligned}$$

The first term in the RHS of $(A.1)$ is

$$\begin{aligned}
E\left[N_1/D\right] &= \frac{\sigma_{vw} tr\left(C'MD\right) - \delta_0 \sigma_v^2 tr\left(C'MC\right)}{\sigma_v^2 tr\left(C'MC\right)} \\
&\quad -2\frac{\sigma_{vw}\sigma_v^2 tr\left(C'MCC'MD\right) - \delta_0 \sigma_v^4 tr\left(C'MCC'MC\right)}{\sigma_v^4 tr\left(C'MC\right)^2} + o\left(T^{-1}\right) \\
&= -\frac{\sigma_{vw}}{\sigma_v^2}\left[\frac{(\rho-\gamma)(1+\gamma)}{(1-\rho\gamma)(1-\rho)} + 2\frac{\gamma(\rho-\gamma)}{(1-\rho\gamma)^2}\right]/T + o\left(T^{-1}\right) \\
&= -\frac{\sigma_{vw}}{\sigma_v^2}\left(\frac{\rho-\gamma}{(1-\rho\gamma)^2(1-\rho)}\right)\left(\frac{1+3\gamma-3\rho\gamma-\rho\gamma^2}{T}\right) + o\left(T^{-1}\right). \qquad \text{(A.8)}
\end{aligned}$$

The second term in the RHS of $(A.1)$ is

$$\begin{aligned}
E\left[N_2/D\right] &= \frac{\sigma_{uv}}{\sigma_v^2}\left(\frac{tr(MC)}{tr\left(C'MC\right)} - 2\frac{tr\left(C'MCMC\right)}{tr\left(C'MC\right)^2}\right) + o\left(T^{-1}\right) \qquad \text{(A.9)} \\
&= -\frac{\sigma_{uv}}{\sigma_v^2}\left(\frac{1+3\gamma}{T}\right) + o\left(T^{-1}\right).
\end{aligned}$$

From $(A.8)$ and $(A.9)$, the bias expression to order T^{-1} is

$$E\left[\hat{\delta} - \delta_0\right] = -\delta_0 \frac{1}{T}\frac{(\rho-\gamma)\left(1-\rho\gamma^2+3\gamma-3\rho\gamma\right)}{(1-\rho\gamma)\left(1-\gamma^2\right)(1-\rho)} - \frac{\sigma_{uv}}{\sigma_v^2}\left(\frac{1+3\gamma}{T}\right) + o\left(T^{-1}\right).$$

B Derivation of the MA coefficient in the ARMA (1,1) return process

Write

$$
\begin{aligned}
r_{t+1} - \rho r_t &= \mu_t - \rho\mu_{t-1} + u_{t+1} - \rho u_t \\
&= u_{t+1} + w_t - \rho u_t = \varepsilon_{t+1} - \theta\varepsilon_t,
\end{aligned}
$$

where ε_t is a white noise process. By the stationarity, we have

$$
\begin{aligned}
\frac{\theta}{1+\theta^2} &= \frac{\sigma_u^2 + \sigma_w^2 + \rho^2\sigma_u^2 - 2\rho\sigma_{uw}}{\rho\sigma_u^2 - \sigma_{uw}} \\
&= \frac{\rho - \rho_{uw}\sqrt{(1-\rho^2)\frac{true\text{-}R^2}{1-true\text{-}R^2}}}{1+\rho^2+(1-\rho^2)\frac{true\text{-}R^2}{1-true\text{-}R^2} - 2\rho\cdot\rho_{uw}\sqrt{(1-\rho^2)\frac{true\text{-}R^2}{1-true\text{-}R^2}}},
\end{aligned}
$$

where the last equality holds since $\left(\sigma_{uw}/\sigma_u^2\right) = \rho_{uw}\sigma_w/\sigma_u$ and $\sigma_w^2 = \sigma_u^2\left(1-\rho^2\right)\left(true\text{-}R^2/\left(1-true\text{-}R^2\right)\right)$. Then, we easily see that $\theta \approx \rho$ when the *true-*R^2 is small and/or ρ is close to one.

C Data Description

Monthly stock market index data are obtained from the website MSCIbarra.com and the international macro-economic data are from both the Organization for Economic Cooperation and Development's (OECD) *Main Economic Indicators: Historical Statistics* and the International Monetary Fund's (IMF) *International Financial Statistics.* Global variables are mostly from the U.S. data and local variables are from the twenty-three countries, whose stock market indices are weighted to produce the MSCI world market index. The variables are as follows; lagged excess returns, dividend yields, inflation lagged three months, relative inflation (the ratio of country's annual inflation to World annual inflation), terms of trade (the ratio of the unit value of exports to the unit value of imports), rates of foreign exchange rate, relative money market rates and 3-month Treasury bill rate (difference between the money market rate (the 3-month T-bill rate) and a 12-month backward-looking moving average), short-rate and term spread, Bond Yield (minus the yield on the long-term goverment bond in excess of its 12-month moving average), narrow and broad money growth (first difference in the log-levels of the narrowly and broadly defined money stock), industrial production growth (first difference in the log-levels of the industrial production index), change in the unemployment rate. Since I do not have access to the *Valuation Ratios*, I construct the proxy variables as follows; the ratios of quarterly real gross domestic product (GDP) per capita and gross national income (GNI) per capita to country's stock market index. As a proxy for the human capital, I build the ratio of wage index to stock market index.

Since the international data series typically suffer from missing values and discontinuities, the autocorrelation parameters are estimated using the longest consecutive periods in which the data are available. For each series, there are at least 46 consecutive observations. A pairwise sample covariance between each pair of variables are computed for the sample covariance matrix, with all of the periods in which the two series overlap. Zero covariances are assumed when there are no overlapping periods for any pair of variables. In order to ensure that the sample covariance matrix constructed above be positive-semidefinite, the sample covariance is decomposed into the product of an orthogonal matrix S and a diagonal matrix Λ such that $\hat{\Sigma} = S'\Lambda S$ and the negative diagonal elements of Λ are set equal to zero.

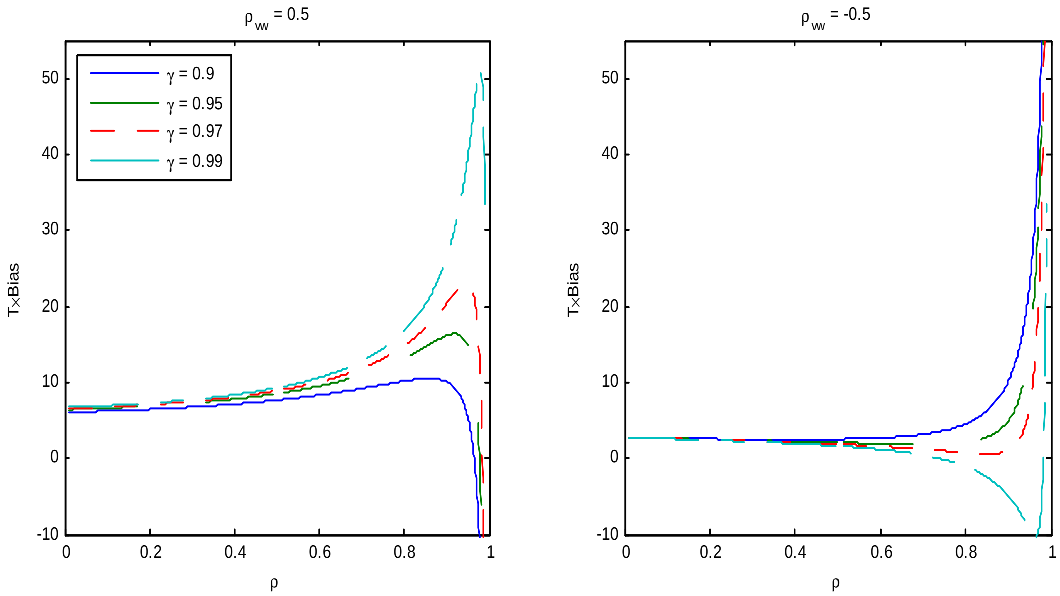

Figure 1: Predicted Finite-sample Bias using formula (5)

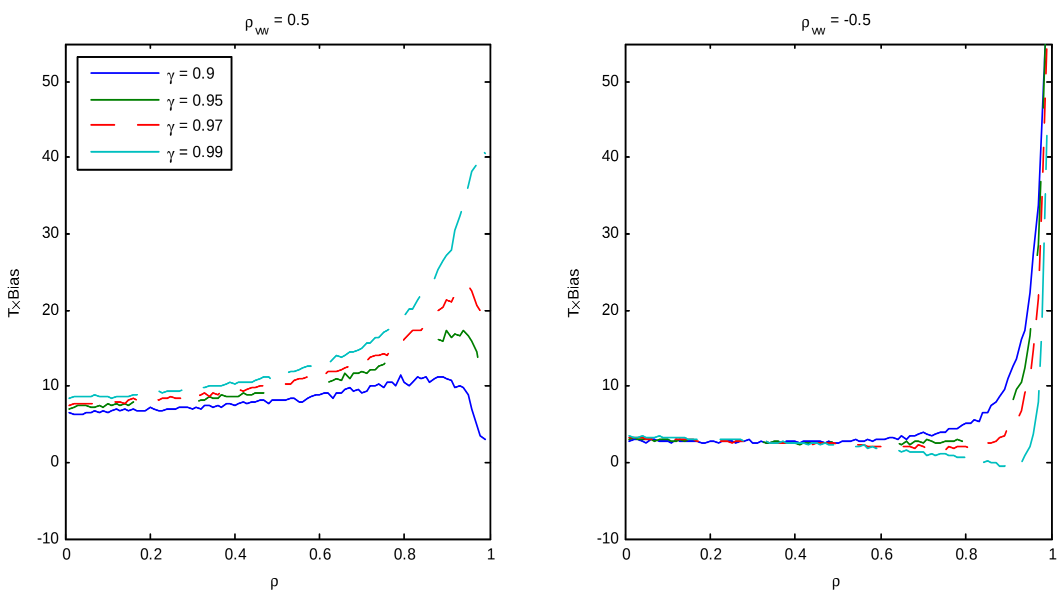

Figure 2: Simulated Finite-sample Bias of OLS estimators

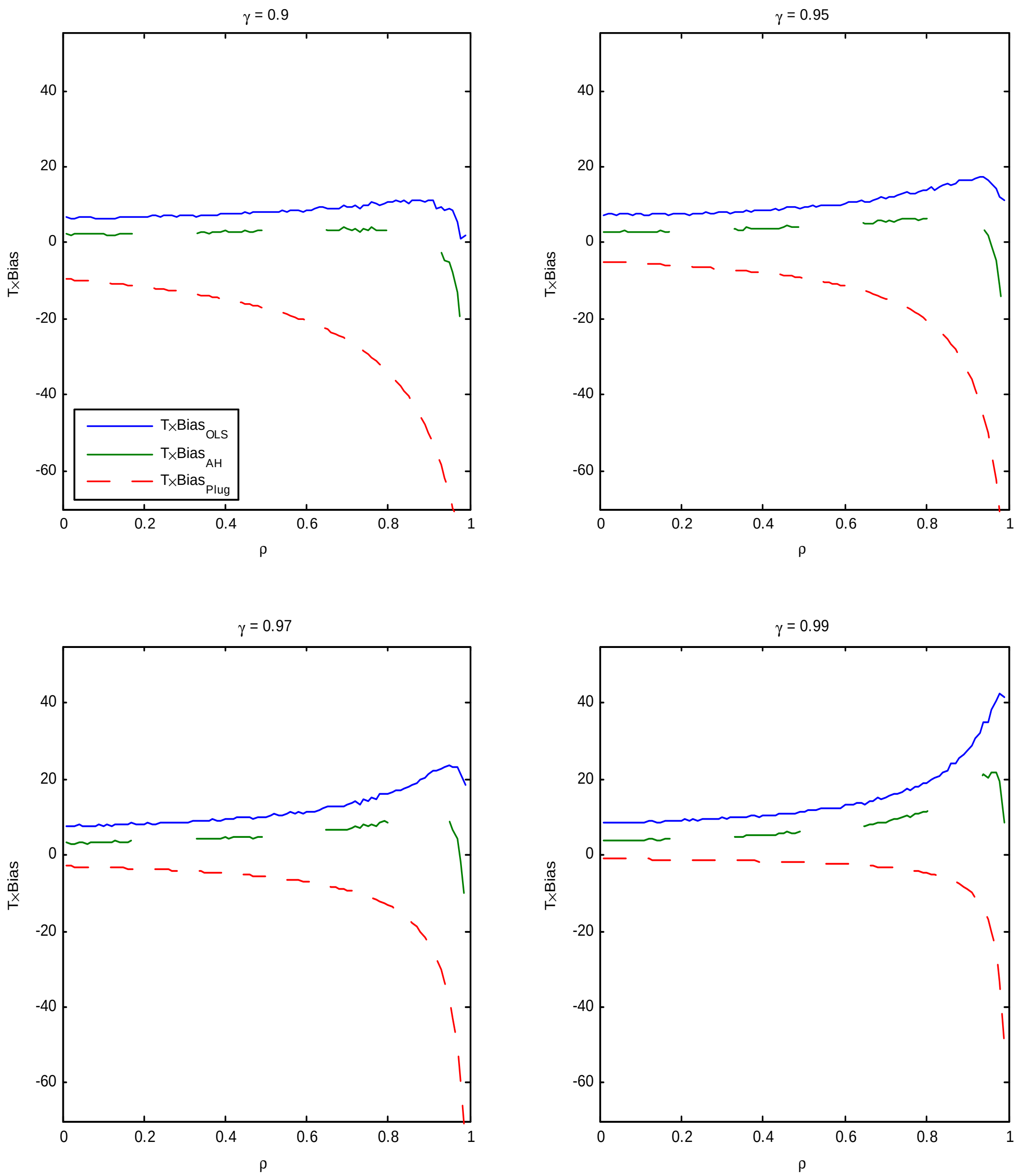

Figure 3: Simulated Performance of Various Estimators (true-validity = 0.5)

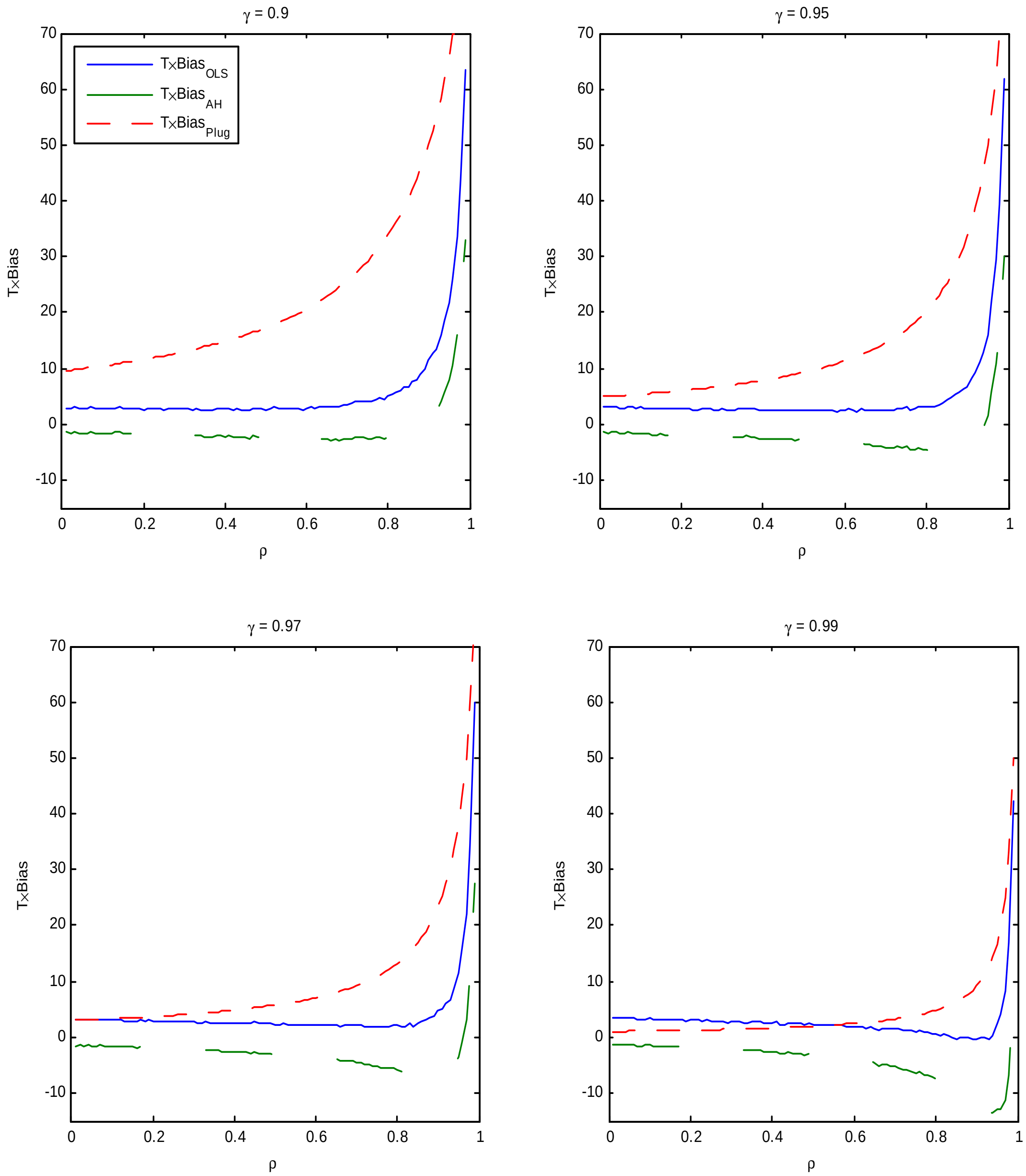

Figure 4: Simulated Performance of Various Estimators (true-validity = -0.5)

Table I
Common Predictive Variables in Published Studies

This table summarizes a list of predetermined regressors for predicting international equity market returns in the literature. The first column indicates selected published studies. The second column documents the number of national equity market returns examined in each study. The next two columns denote the lagged predictors, global and local. The last two columns show the sample period and the number of observations. The abbreviations in the table are as follows. *ConsRatio* is the rate of U.S. consumption change lagged 3 months. *Div_wrd, Div_SP, Div_US, Div_loc* are the dividend yields on the world market index, the S&P 500, the MSCI U.S. stock market index or the local stock market indices. *TB1y* and *TB3r* are the yield and the excess return on a one-month and 3-month U.S. T-bill. *Def* and *TED* are the spreads for the U.S. default risk yield and the 90-day Eurodollar-U.S. Treasury bill. *Rg10fx* is the excess return to holding the currency portfolios of 10 industrialized countries. *Term_US* and *E$Term* are the yields spread between 10-year Treasury bonds and 90-day T-bill and between a 90-day and a 30-day Eurodollar deposit rate. *E$30* is the 30-day Eurodollar deposit rate and *By_US* is the yield on a U.S. bond price index. *MonP* is an ex-ante, binary measure of monetary conditions. *Short* and *Long* are short-term and long-term local interest rates, whereas their difference is denoted by *Term*. *Euro* is the one-month Euro-currency interest rate and *GovBY* is the long-term government bond yields. For each country, *TOT* is the terms of trade and *INF* is the lagged quarterly inflation. *rGDP* is the ratio of per capita national GDP to OECD GDP. *RMM*, *RTB*, and *RGB* are the money market interest rate, 3-month T-bill rate, and long-term government bond yield, each of which are detrended with 12-month moving averages. Two more recent variables are considered in the last two rows; *Cay* is the log "consumption-aggregate wealth ratio" and *BondYield* is minus the moving average detrended yield on the 30-year Treasury bond.

(1) Reference	(2) Country	(3) Global Predictor	(4) Local Predictor	(5) Period	(6) Obs
Cumby (1990)	4 countries	*ConsRatio*	*Div_loc*	7404-8712	165
			TOT	7404-8712	165
			CPI	7404-8712	165
Harvey (1991)	World Return	*Div_SP*	*Div_loc*	7002-8905	232
	17 countries	*TB3r*		7002-8905	232
	(OECD + HK)	*Def*		7002-8905	232
		Wrd		7002-8905	232
Ferson & Harvey (1993)	World return	*Div_wrd*	*Div_loc*	7002-8912	239
	18 Countries	*TED*	*Term*	7002-8912	239
		Term_US	*Short*	7002-8912	239
		TB1y		7002-8912	239
		Wrd		7002-8912	239
Solnik (1993)	8 countries		*Div_loc*	7101-9008	236
			Euro	7101-9008	236
			GovBY	7101-9008	236
Ferson & Harvey (1994)	World Return	*Rg10fx*	*Div_loc*	7601-9301	205
	21 countries	*Div_wrd*	*rGDP*	7601-9301	205
		E$Term	*Long*	7601-9301	205
		E$30		7601-9301	205
		Wrd		7601-9301	205
Dumas & Solnik (1995)	World Return	*Div_US*		7003-9112	262
	4 countries	*E$30*		7003-9112	262
		By_US		7003-9112	262
Conover, Jensen, & Johnson (1999)	16 countries	*MonP_US*	*MonP_loc*	5601-9512	247~480
Rapach, Wohar, & Rangvid (2005)	12 countries		*RMM*	7002-0206	227~389
			RTB	7002-0206	227~389
			RGB	7002-0206	227~389
			INF	7002-0206	227~389
Ang & Bekaert (2007)	4 countries	*E$30*	*Div_loc*	7502-0112	323
Lettau & Ludvigson (2001)	U.S.	*Cay*		70Q1-06Q4	148
Pastor & Stambaugh (2006)	U.S.	*BondYield*		7001-0612	444

Table II

OLS Regressions of the World Market Return on Global Predictors

This table provides summary statistics for global predictors used in the literature. The first column indicates predetermined, lagged predictors. The next two columns give the sample period and the number of observations. The fourth and fifth column report the estimates for autocorrelation parameter (ρ_z) and standard deviation (σ_z). The next two columns report slope coefficient estimates of δ from the OLS (δ_{OLS}) and Reduced-Bias estimation method (δ_{AH}) proposed by Amihud & Hurvich (2004). The t-statistics testing the null hypothesis H_0: $\delta = 0$ are reported in the next columns, where t_{HAC} is calculated with the Newey-West (1987) standard error estimators and t_{AH} is calculated with the procedures in Amihud, Hurvich & Wang (2008). The next column reports the adjusted-coefficient of determination, R^2. The column with Corr(u,v) reports the estimated contemporaneous correlation between the regression residuals and the stochastic regressor's autoregressive innovations. The last column reports the number of lags for the Newey-West (1987) standard error estimators, determined by Andrew (1991)'s data-dependent selection rules.

(1) Global Predictor	(2) Period	(3) Obs	(4) ρ_z	(5) σ_z	(6) δ_{OLS}	(7) δ_{AH}	(8) t_{HAC}	(9) t_{AH}	(10) R^2	(11) Corr(u,v)	(12) HAC
$ConsRatio_{t-1}$	7404-8712	165	0.611	0.006	0.393	0.430	0.677	0.722	-0.004	0.074	2
Div_SP_{t-1}	7002-8905	232	0.951	0.007	0.587	0.333	1.286	0.835	0.005	-0.711	3
$TB3r_{t-1}$	7002-8905	232	0.224	0.001	7.732	7.804	4.070	4.074	0.062	0.112	1
Def_{t-1}	7002-8905	232	0.943	0.005	1.479	1.501	2.051	2.456	0.021	0.109	3
Div_wrd_{t-1}	7101-8912	228	0.974	0.009	0.034	-0.263	0.093	-0.851	-0.004	-0.741	2
TED_{t-1}	7002-8912	239	0.857	0.009	-0.683	-0.709	-1.643	-2.459	0.019	-0.248	3
$Term_{t-1}$	7002-8912	239	0.926	0.014	0.490	0.517	2.522	2.699	0.023	0.150	2
$TB1y_t$	7002-8912	239	0.942	0.027	-0.302	-0.310	-3.149	-3.101	0.033	-0.115	1
wrd_{t-1}	7002-8912	239	0.140	0.042	0.142	N/A	2.123	N/A	0.016	N/A	0
$Rg10fx_{t-1}$	7601-9301	205	0.311	0.023	-0.071	-0.076	-0.532	-0.583	-0.004	-0.267	2
$E\$Term_{t-1}$	7601-9301	205	0.524	0.003	1.007	0.963	1.043	0.931	0.000	-0.188	2
$DivUS\_E\$30_{t-1}$	7102-9112	251	0.937	0.027	0.328	0.325	3.558	3.283	0.038	0.085	1
$MonP\_US_{t-1}$	7002-9512	311	0.906	0.500	0.017	0.018	4.063	3.861	0.041	0.103	1
$E\$30_t$	7502-0112	323	0.972	0.034	-0.131	-0.133	-1.966	-1.989	0.009	0.000	0
$BondYield_{t-1}$	7001-0612	444	0.898	0.007	1.220	1.241	5.340	4.673	0.043	0.198	3
Cay_{t-1}	70Q1-06Q4	148	0.867	0.015	1.077	0.948	2.888	2.067	0.030	-0.496	1

Table III
Distribution of γ and ρ_{uv} in the Set of Potential Predictors

This table summarizes statistics of 385 potential predictors which consist of county-specific measures of valuation ratios, interest rates and other macro-economic variables. The parameter γ is the first-order autocorrelation coefficient of the predictors and ρ_{uv} is the correlation between the unexpected stock return and the predictor's autoregressive residuals. In order to calculate ρ_{uv}, the correlation between the stock return and the estimated predictor's autoregressive residuals is used as a proxy. The first panel summarizes statistics with sorting by γ or ρ_{uv} and the second panel sorts the variables based on two-way sorts of γ and ρ_{uv}.

Panel 1: Distributions of Key Parameters

γ		ρ_{uv}	
mean	0.688	mean	-0.075
median	0.916	median	-0.041
min	-0.388	min	-0.752
max	0.990	max	0.858
number of $\gamma \geq 0.97$	130 (34%)	number of positive ρ_{uv}	142 (37%)
number of $\gamma \geq 0.95$	162 (42%)	number of negative ρ_{uv}	243 (63%)
number of $\gamma \geq 0.90$	204 (53%)	number of $\rho_{uv} \geq 0.5$	18 (5%)
		number of $\rho_{uv} \leq -0.5$	22 (6%)
upper quartile	0.987	upper quartile	0.038
lower quartile	0.348	lower quartile	-0.216

Panel 2: Sorting on γ and ρ_{uv}

$\gamma \backslash \sigma_{uv}$	$\rho_{uv} < -0.5$	$-0.5 \leq \rho_{uv} < -0.3$	$-0.3 \leq \rho_{uv} < 0.3$	$0.3 \leq \rho_{uv} < 0.5$	$\rho_{uv} \geq 0.5$
		a. Number of predictors			
$\gamma \geq 0.95$	22	48	92	0	0
$0.9 \leq \gamma < 0.95$	0	2	40	0	0
$\gamma < 0.9$	0	0	158	5	18
		b. $E[\gamma]$			
$\gamma \geq 0.95$	0.986	0.983	0.979		
$0.9 \leq \gamma < 0.95$		0.926	0.925		
$\gamma < 0.9$			0.417	0.045	0.064
		c. $E[\rho_{uv}]$			
$\gamma \geq 0.95$	-0.619	-0.417	-0.051		
$0.9 \leq \gamma < 0.95$		-0.376	0.006		
$\gamma < 0.9$			-0.023	0.416	0.536

Table IV

Simulation Results for the bias-adjusted estimators

The table provides summary statistics for bias-adjusted estimators for δ in the regression model (1) from 10,000 simulation replications. The 'Avg' column reports average bias of each estimator corrected for the first-order bias and the 'MSE' column reports mean squared errors of the bias. True coefficient δ_0 is assumed to be known. The table shows statistics for the values of $(\hat{\delta} - \delta_0 - \mathrm{B})$ where B is the first-order bias formula. The values in the 'Eq.(5)' row are bias-adjusted with the formula (5) whereas the values in the 'Stamb' row are bias-adjusted following Stambaugh (1999). γ and ρ are the autocorrelation parameters for the measured and true predictor and δ_0 indicates the true coefficient. The true-validity is set to 0.95 and the *true-R*^{2} is set to 0.05.

Panel 1: 148 Observations

	Estimator	$\rho_{uv} = -0.9$		$\rho_{uv} = -0.5$		$\rho_{uv} = 0.5$		$\rho_{uv} = 0.9$	
		A. ρ = 0.15							
		Avg	MSE	Avg	MSE	Avg	MSE	Avg	MSE
$\gamma = 0.9$ ($\delta_0 = 0.21$)	Eq.(5)	-0.064	0.052	-0.038	0.044	0.021	0.030	0.046	0.027
	Stamb	-0.038	0.051	-0.013	0.043	0.044	0.032	0.069	0.031
$\gamma = 0.95$ ($\delta_0 = 0.11$)	Eq.(5)	-0.064	0.038	-0.039	0.031	0.022	0.020	0.045	0.020
	Stamb	-0.036	0.036	-0.011	0.030	0.049	0.022	0.071	0.023
$\gamma = 0.97$ ($\delta_0 = 0.07$)	Eq.(5)	-0.061	0.030	-0.038	0.024	0.024	0.016	0.048	0.016
	Stamb	-0.032	0.028	-0.009	0.023	0.052	0.018	0.075	0.020
		B. ρ = 0.95							
		Avg	MSE	Avg	MSE	Avg	MSE	Avg	MSE
$\gamma = 0.9$ ($\delta_0 = 1.24$)	Eq.(5)	0.031	0.921	0.089	1.041	0.212	1.293	0.292	1.431
	Stamb	-0.144	0.972	-0.087	1.050	0.035	1.262	0.113	1.398
$\gamma = 0.95$ ($\delta_0 = 0.95$)	Eq.(5)	-0.181	0.298	-0.103	0.253	0.081	0.253	0.156	0.280
	Stamb	-0.178	0.304	-0.101	0.255	0.079	0.256	0.153	0.286
$\gamma = 0.97$ ($\delta_0 = 0.72$)	Eq.(5)	-0.233	0.298	-0.161	0.231	0.032	0.180	0.115	0.186
	Stamb	-0.124	0.266	-0.053	0.212	0.136	0.200	0.217	0.226

Panel 2: 972 Observations

	Estimator	$\rho_{uv} = -0.9$		$\rho_{uv} = -0.5$		$\rho_{uv} = 0.5$		$\rho_{uv} = 0.9$	
		A. ρ = 0.15							
		Avg	MSE	Avg	MSE	Avg	MSE	Avg	MSE
$\gamma = 0.9$ ($\delta_0 = 0.21$)	Eq.(5)	-0.009	0.007	-0.005	0.006	0.003	0.004	0.007	0.003
	Stamb	-0.005	0.007	-0.002	0.006	0.006	0.004	0.011	0.004
$\gamma = 0.95$ ($\delta_0 = 0.11$)	Eq.(5)	-0.009	0.004	-0.005	0.004	0.003	0.003	0.006	0.002
	Stamb	-0.005	0.004	-0.001	0.004	0.007	0.003	0.010	0.002
$\gamma = 0.97$ ($\delta_0 = 0.07$)	Eq.(5)	-0.010	0.003	-0.005	0.003	0.003	0.002	0.007	0.002
	Stamb	-0.005	0.003	-0.001	0.003	0.007	0.002	0.011	0.002
		B. ρ = 0.95							
		Avg	MSE	Avg	MSE	Avg	MSE	Avg	MSE
$\gamma = 0.9$ ($\delta_0 = 1.24$)	Eq.(5)	-0.014	0.043	-0.004	0.048	0.021	0.060	0.036	0.066
	Stamb	-0.031	0.043	-0.020	0.048	0.004	0.060	0.019	0.065
$\gamma = 0.95$ ($\delta_0 = 0.95$)	Eq.(5)	-0.029	0.033	-0.014	0.033	0.017	0.032	0.026	0.033
	Stamb	-0.029	0.033	-0.014	0.033	0.017	0.033	0.026	0.033
$\gamma = 0.97$ ($\delta_0 = 0.72$)	Eq.(5)	-0.033	0.031	-0.022	0.028	0.007	0.022	0.017	0.021
	Stamb	-0.017	0.031	-0.006	0.027	0.023	0.022	0.033	0.022

Table V

Simulation Results for Regression Model (1) with a Lagged Predictive Variable

The table reports the 95 percentile of the empirical distribution for the Newey-West (1994) t-statistics testing the null hypothesis that the slope coefficient for the predictive regression (1) is equal to zero. The parameter γ is the autocorrelation coefficient of the predictive variable and ρ_{uv} is the correlation between the unexpected stock return and the predictor's autoregressive residuals. The *true-R^2* represents the actual fraction of predictable variability in the stock return, based on the unobserved conditional expected return. The autocorrelation parameter for the underlying expected return, ρ, is set equal to γ.

Panel 1: 148 Observations

γ/ρ_{uv}	-0.9	-0.5	0	0.5	0.9
			A. true-R^2 = 0.001		
0	1.8392	1.7651	1.7546	1.6605	1.6600
0.5	1.9274	1.8737	1.7228	1.6094	1.5630
0.9	2.1563	1.9559	1.6997	1.4462	1.2089
0.95	2.3578	2.1315	1.7636	1.2919	0.9710
0.97	2.4222	2.1864	1.7171	1.2484	0.7700
0.99	2.6882	2.3396	1.7808	0.9926	0.4399
			B. true-R^2 = 0.05		
0	1.8276	1.7595	1.7358	1.6888	1.6360
0.5	1.9057	1.8237	1.7286	1.6275	1.5646
0.9	2.3725	2.2062	1.9684	1.7616	1.5335
0.95	2.6815	2.4941	2.1057	1.7881	1.4704
0.97	2.8668	2.6662	2.1919	1.7437	1.3831
0.99	3.1153	2.7173	2.1851	1.5824	1.0225
			C. true-R^2 = 0.15		
0	1.8369	1.7828	1.6967	1.6902	1.6333
0.5	1.9120	1.8419	1.7530	1.6914	1.5492
0.9	2.7282	2.5606	2.3258	2.1099	1.9005
0.95	3.2669	3.0028	2.7608	2.4279	2.1569
0.97	3.5666	3.3149	2.8846	2.5971	2.2460
0.99	3.7871	3.3932	2.9005	2.3931	1.8320

Panel 2: 972 Observations

γ/ρ_{uv}	-0.9	-0.5	0	0.5	0.9
			A. true-R^2 = 0.001		
0	1.6766	1.6944	1.6366	1.6404	1.5988
0.5	1.7133	1.6802	1.6019	1.5977	1.5816
0.9	1.8294	1.7479	1.6670	1.5195	1.5021
0.95	1.9311	1.8251	1.6705	1.5385	1.3987
0.97	2.0257	1.8806	1.6836	1.4943	1.3279
0.99	2.2459	2.0379	1.6904	1.3829	1.0804
			B. true-R^2 = 0.05		
0	1.6892	1.7026	1.6408	1.6825	1.6369
0.5	1.7909	1.6980	1.6630	1.5965	1.6047
0.9	2.0412	1.9911	1.8896	1.8440	1.7520
0.95	2.3978	2.2710	2.2633	2.0218	1.9944
0.97	2.7511	2.5890	2.4828	2.3698	2.1998
0.99	3.8514	3.6135	3.3674	3.0832	2.9653
			C. true-R^2 = 0.15		
0	1.7073	1.6480	1.6629	1.6356	1.6522
0.5	1.7719	1.7560	1.6826	1.6582	1.6284
0.9	2.3362	2.2761	2.1227	2.0541	2.0459
0.95	2.8176	2.7274	2.7005	2.5486	2.4890
0.97	3.4605	3.3277	3.2244	3.0856	2.9962
0.99	5.2169	5.0972	4.9185	4.6811	4.5526

Table VI
Simulation Results for Data Mining with different numbers of Potential Regressors in the presence of Spurious Regression and Lagged Stochastic Regressor Bias

The table reports the 95 percentile of the empirical distribution for the Newey-West t-statistics testing the null hypothesis that the slope coefficient for the predictive regression (1) is equal to zero. The *true-R^2* is the coefficient of determination from the regression of excess return on the underlying expected return, where the unobserved expected return follows a first-order autoregression with the persistence parameter ρ set equal to 0.15 for the columns of "Pure Mining" and "Lagged Regressors Bias" or 0.95 for the columns of "Spurious" and "Spurious and Lagged Regressor Bias". The parameter M is the number of regressors through which analysts are searching for the one with the highest estimated t-statistic. For the Negative ρ_{uv} column, ρ_{uv}'s are normally distributed around -0.5 whereas ρ_{uv}s are around 0.5 for the Positive ρ_{uv} column.

Panel 1: 148 Observations

M	Pure Mining	Spurious	Lagged Regressor Bias		Spurious and Lagged Regressor Bias	
			Positive ρ_{uv}	Negative ρ_{uv}	Positive ρ_{uv}	Negative ρ_{uv}
A. true-R^2 = 0.05						
1	1.7174	2.2927	0.6051	2.8569	1.2712	3.4207
5	2.4621	3.0193	2.0434	3.1255	2.3472	3.6732
10	2.8260	3.4460	2.2159	4.1481	2.5627	4.8289
25	3.2394	3.9115	2.7113	4.6342	3.0973	5.4637
50	3.8022	4.6969	3.0050	5.5380	3.4420	6.3988
100	4.3175	5.3092	3.2945	6.6904	3.9031	7.8929
250	5.1098	6.3551	3.7320	7.8652	4.5182	9.0274
B. true-R^2 = 0.15						
1	1.7557	3.0528	0.6829	2.8618	2.0700	4.1844
5	2.5143	3.9276	2.0208	3.1419	3.1243	4.3826
10	2.8417	4.5549	2.2360	4.1713	3.3999	5.7203
25	3.2152	5.0780	2.7338	4.7028	4.0299	6.4121
50	3.8276	6.2438	3.0312	5.3951	4.7868	7.7320
100	4.3977	7.0012	3.3584	6.6945	5.4966	9.0800
250	5.0781	8.2429	3.7826	7.8260	6.1875	10.5407

Panel 2: 972 Observations

M	Pure Mining	Pure Spurious	Pure Lagged Regressor Bias		Spurious and Lagged Regressor Bias	
			Positive ρ_{uv}	Negative ρ_{uv}	Positive ρ_{uv}	Negative ρ_{uv}
A. true-R^2 = 0.05						
1	1.6287	2.5148	1.1066	2.2519	1.9892	3.0645
5	2.3560	3.2591	2.0304	2.5439	2.7142	3.3324
10	2.5807	3.4983	2.2429	2.8404	2.8331	3.7647
25	2.8951	3.8316	2.6316	3.1404	3.2738	4.1337
50	3.0763	4.0237	2.8383	3.3195	3.6516	4.3945
100	3.2868	4.3289	3.0761	3.5846	3.9605	4.6554
250	3.5491	4.6742	3.4044	3.8647	4.3296	5.0929
B. true-R^2 = 0.15						
1	1.7051	3.1444	1.1190	2.2574	2.8266	3.6599
5	2.3769	4.1563	2.0534	2.5294	3.6122	4.0194
10	2.5962	4.6096	2.2450	2.8223	3.8957	4.6695
25	2.8995	5.0662	2.6201	3.1227	4.3536	5.0932
50	3.0941	5.2744	2.8846	3.3223	4.7665	5.4976
100	3.2916	5.7178	3.0698	3.5701	5.2637	5.9698
250	3.5867	6.2234	3.3883	3.8306	5.7820	6.5059

Table VII
Empirical Re-evaluation of the International Equity Market Return Predictability

The table reports the re-evaluation results of empirical evidence in international market return predictability. Panel 1 revisits the prediction results in Table II from regressing each global predictor against the world market return at a time. The 95 percentile empirical critical values are calculated for both the t-statistics, t^{HAC} and t^{AH} ,from the Monte Carlo simulations similar to Table VI given sample sizes, autocorrelations, and *discount-rate effect correlations* in the first three columns. It is assumed that analysts set the one-sided alternative hypothesis in accordance with the sign of estimated slope coefficients and the left-tail critical values are reported when the estimated t-statistics are negative. The last three columns report the minimum numbers of searches in the set of independent regressors to find a t-statistic at least as high as the reported values of estimated t^{HAC}. Three different sets of potential predictors are considered. The numbers in M column are calculated with the predictors whose residuals are generated with the actual estimated *discount-rate effect correlations*, while the correlations are normally distributed around -0.5 and +0.5 for the numbers in the M- and M+ columns. As in Table VII, the maximum number of data mining is set to 250 and if the estimated t-statistic is larger than the one obtainable with the maximum number of data mining, the value is reported to be > 250. Panel 2 investigates the predictability of the eighteen national market returns using the global and country-specific variables considered in past studies. The reported numbers are the total number of univariate regressions followed by the number of predictors with significant slope coefficient estimates from the perspective of traditional measures or simulated critical values. Then the largest values of t^{HAC} are reported with the regressor's autocorrelation and *discount-rate effect correlations*, and finally, the last three columns report the minimum required numbers of data mining in three different potential predictor sets to achieve the acquired largest t-statistics. For simulations in Panel 1 and 2, the autocorrelation of underlying expected return, ρ, is set to γ and the *true*-R^2 is set to 0.1.

Panel 1: Table II Simulation

Obs	γ	ρ_{uv}	t^{HAC}	Critical t^{HAC}	t^{AH}	Critical t^{AH}	M	M^-	M^+
165	0.61	0.07	0.677	1.798	0.722	1.754	1	1	1
232	0.95	-0.71	1.286	2.800	0.835	2.447	1	1	1
232	0.22	0.11	4.070	1.752	4.074	1.660	109	23	> 250
232	0.94	0.11	2.051	2.332	2.456	2.500	1	1	2
228	0.97	-0.74	0.093	3.161	-0.851	-3.072	1	1	1
239	0.86	-0.25	-1.643	-1.918	-2.459	-2.027	1	2	1
239	0.93	0.15	2.522	2.186	2.699	2.337	2	1	3
239	0.94	-0.12	-3.149	-2.337	-3.101	-2.463	3	8	1
239	0.14	0.00	2.123	1.713	N/A	N/A	3	1	10
205	0.31	-0.27	-0.532	-1.686	-0.583	-1.716	1	2	1
205	0.52	-0.19	1.043	1.757	0.931	1.697	1	1	2
251	0.94	0.09	3.558	2.235	3.283	2.394	6	1	24
311	0.91	0.10	4.063	2.068	3.861	2.260	21	7	91
323	0.97	0.00	-1.966	-2.843	-1.989	-2.954	1	1	1
444	0.90	0.20	5.340	1.983	4.673	2.252	> 250	76	> 250
148	0.87	-0.50	2.888	2.220	2.067	2.044	4	1	19

Panel 2: International Market Return Predictability

Country	# of Regressors	Significant t^{HAC}		Significant t^{AH}		Largest t	γ	ρ_{uv}	M	M^-	M^+
		Theoretical	Actual	Theoretical	Actual						
Australia	31	10	6	11	5	5.234	0.98	-0.85	21	8	72
Austria	32	8	4	11	4	3.830	0.90	0.03	21	7	82
Belgium	31	11	6	14	8	4.166	0.90	0.12	40	11	151

Canada	33	10	5	9	5	3.794	0.24	0.04	201	52	> 250
Denmark	33	10	5	10	4	-3.227	0.91	0.00	5	13	2
France	33	5	1	8	2	2.829	0.90	0.08	4	1	11
Germany	33	8	4	7	4	4.129	0.90	0.10	36	11	122
HongKong	17	5	1	5	1	2.560	0.96	-0.11	1	1	7
Holland	32	15	10	16	9	-4.368	0.90	0.03	50	155	2
Italy	32	6	4	5	3	4.342	0.98	-0.73	5	4	18
Japan	33	15	9	14	7	2.957	0.90	0.06	4	1	14
Norway	32	5	2	5	1	2.751	0.90	0.06	2	1	7
Singapore	30	9	2	8	4	3.522	0.24	0.01	101	25	> 250
Spain	33	15	3	14	3	-3.022	0.99	-0.06	1	5	1
Sweden	33	5	5	6	5	-3.407	0.22	-0.11	76	212	11
Swiss	32	11	7	12	7	4.297	0.90	0.19	45	21	164
UK	33	9	3	9	3	3.130	0.24	0.07	35	8	100
USA	31	16	8	16	6	3.723	0.90	0.25	15	7	67
Total	564	173 (31%)	85 (15%)	180 (32%)	81 (14%)						

Table A.1

OLS Regressions of the national market returns on Global Predictors

This table summarizes predictive regression results for 18 national market returns using common predictors in table II with corresponding sample periods. δ_{OLS} and t_{HAC} are the OLS slope coefficient estimate and t-statistic calculated with the Newey-West (1987) standard error estimators. The reduced-bias slope coefficient estimate δ_{AH} and the t-statistic, t_{AH}, are constructed using the procedures proposed by Amihud & Hurvich (2004) and Amihud, Hurvich & Wang (2008). The R^2 is the adjusted-coefficient of determination and Corr(u,v) is the sample correlation between the regression residuals and the regressor's autoregressive innovations. Maximum and minimum of Corr(u,v) are documented in the first column. The t-statistics are bolded for the values larger than |1.65|.

		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.117	0.261	0.261	0.912	0.088	0.900	-0.178	-0.775	0.061
	δ_{AH}	0.143	0.307	0.280	0.967	0.110	0.885	-0.177	-0.678	0.024
	t_{HAC}	0.104	0.346	0.314	0.960	0.125	0.816	-0.232	-0.524	0.060
	t_{AH}	0.120	0.402	0.327	1.111	0.152	0.842	-0.214	-0.447	0.021
$ConsRatio_{t-1}$	R^2	-0.006	-0.005	-0.006	0.001	-0.006	-0.002	-0.006	-0.005	-0.006
	Corr(u,v)	0.018	0.023	0.022	0.024	0.076	-0.027	-0.024	0.114	-0.005
Max(ρ_{uv}): 0.114		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.070	δ_{OLS}	0.633	0.260	1.284	-1.141	0.065	0.651	0.022	-0.184	0.376
	δ_{AH}	0.656	0.312	1.293	-1.094	0.084	0.687	0.028	-0.136	0.440
	t_{HAC}	0.837	0.298	0.986	-0.877	0.081	0.747	0.024	-0.139	0.597
	t_{AH}	0.780	0.391	1.107	-0.854	0.085	0.760	0.035	-0.116	0.642
	R^2	-0.003	-0.005	0.001	-0.001	-0.006	-0.003	-0.006	-0.006	-0.004
	Corr(u,v)	0.094	0.034	-0.004	0.034	-0.070	0.024	-0.004	-0.065	0.100
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.703	-0.878	0.012	0.840	-0.319	0.953	0.317	-1.272	0.124
	δ_{AH}	0.433	-0.958	-0.167	0.562	-0.480	0.734	0.165	-1.592	0.018
	t_{HAC}	0.816	**-1.788**	0.021	1.304	-0.560	1.193	0.563	-0.749	0.175
	t_{AH}	0.550	**-1.877**	-0.291	0.998	-0.908	1.048	0.289	-1.323	0.024
$DivSP_{t-1}$	R^2	-0.001	0.008	-0.004	0.005	-0.003	0.004	-0.003	0.000	-0.004
	Corr(u,v)	-0.385	-0.137	-0.319	-0.589	-0.318	-0.341	-0.272	-0.250	-0.128
Max(ρ_{uv}):-0.128		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.830	δ_{OLS}	-1.214	0.780	-0.557	-0.193	-1.628	0.192	0.397	1.512	1.136
	δ_{AH}	-1.369	0.533	-0.855	-0.456	-1.808	-0.007	0.163	1.235	0.842
	t_{HAC}	**-1.725**	1.366	-0.564	-0.154	**-2.787**	0.347	0.687	**1.879**	**2.280**
	t_{AH}	**-2.383**	1.008	-1.080	-0.503	**-2.957**	-0.012	0.301	**1.647**	**1.891**
	R^2	0.015	0.005	-0.002	-0.004	0.026	-0.004	-0.002	0.013	0.024
	Corr(u,v)	-0.240	-0.495	-0.398	-0.344	-0.297	-0.371	-0.437	-0.382	-0.830
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	11.637	1.651	7.198	11.659	1.610	3.593	4.539	3.399	2.770
	δ_{AH}	11.664	1.706	7.299	11.694	1.690	3.688	4.622	3.564	2.844
$TB3r_{t-1}$	t_{HAC}	**2.802**	0.701	**2.178**	**4.032**	0.792	0.986	**1.828**	0.423	0.904
	t_{AH}	**3.039**	0.668	**2.591**	**4.335**	0.643	1.058	1.636	0.595	0.771
Max(ρ_{uv}): 0.133	R^2	0.034	-0.003	0.023	0.071	-0.003	0.000	0.007	-0.003	-0.002
Min(ρ_{uv}):-0.051	Corr(u,v)	-0.047	0.028	0.114	0.074	0.108	0.109	0.081	0.010	0.020
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	1.331	7.470	2.930	12.449	3.479	4.227	6.393	10.146	9.131
	δ_{AH}	1.445	7.570	3.023	12.474	3.521	4.293	6.526	10.285	9.128
	t_{HAC}	0.513	**2.738**	0.546	**3.179**	0.984	1.570	**2.293**	**2.780**	**3.718**

	t_{AH}	0.501	**2.922**	0.769	**2.813**	1.143	1.460	**2.459**	**2.782**	**4.246**
	R^2	-0.003	0.030	-0.002	0.029	0.001	0.005	0.020	0.027	0.068
	Corr(u,v)	0.075	0.090	0.031	0.040	-0.051	0.086	0.133	0.090	0.090
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.989	-1.822	0.060	1.015	0.597	-0.089	0.638	0.123	0.067
	δ_{AH}	0.976	-1.860	0.064	1.038	0.575	-0.106	0.626	-0.014	0.059
	t_{HAC}	0.891	**-2.263**	0.062	1.071	0.750	-0.075	0.785	0.050	0.051
	t_{AH}	0.800	**-2.361**	0.072	1.190	0.702	-0.097	0.707	-0.008	0.051
Def_{t-1}	R^2	-0.001	0.018	-0.004	0.002	-0.002	-0.004	-0.002	-0.004	-0.004
	Corr(u,v)	0.021	0.020	0.083	0.032	0.028	0.034	0.049	0.005	0.055
Max(ρ_{uv}): 0.145		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}): 0.005	δ_{OLS}	0.480	1.161	-1.559	0.813	-0.827	2.043	0.307	1.958	1.948
	δ_{AH}	0.429	1.198	-1.633	0.903	-0.852	2.052	0.306	1.975	2.043
	t_{HAC}	0.449	1.296	-1.120	0.469	-0.909	**2.065**	0.309	1.588	**2.866**
	t_{AH}	0.477	1.461	-1.335	0.642	-0.886	**2.251**	0.365	**1.694**	**2.988**
	R^2	-0.003	0.004	0.003	-0.003	-0.001	0.017	-0.004	0.008	0.030
	Corr(u,v)	0.039	0.145	0.005	0.075	0.044	0.042	0.119	0.103	0.104
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	-0.168	-1.248	-0.571	0.116	-0.468	-0.152	-0.079	-0.423	-0.485
	δ_{AH}	-0.476	-1.185	-0.837	-0.185	-0.671	-0.411	-0.181	-0.841	-0.649
	t_{HAC}	-0.231	**-2.809**	-1.181	0.242	-1.093	-0.253	-0.162	-0.428	-0.865
	t_{AH}	-0.785	**-2.888**	**-1.864**	-0.431	-1.597	-0.749	-0.407	-0.888	-1.120
Div_wrd_{t-1}	R^2	-0.004	0.033	0.003	-0.004	0.001	-0.004	-0.004	-0.004	-0.001
	Corr(u,v)	-0.409	-0.243	-0.467	-0.524	-0.415	-0.464	-0.443	-0.309	-0.270
Max(ρ_{uv}):-0.243		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.637	δ_{OLS}	-0.567	0.127	-0.969	-0.025	-1.514	-0.184	0.107	0.646	0.285
	δ_{AH}	-0.912	-0.134	-1.219	-0.311	-1.748	-0.387	-0.202	0.319	0.000
	t_{HAC}	-1.115	0.285	-1.404	-0.030	**-3.117**	-0.393	0.228	0.929	0.684
	t_{AH}	**-2.011**	-0.326	**-1.980**	-0.441	**-3.717**	-0.856	-0.472	0.542	-0.001
	R^2	0.003	-0.004	0.007	-0.004	0.041	-0.004	-0.004	0.001	-0.001
	Corr(u,v)	-0.503	-0.593	-0.391	-0.348	-0.362	-0.470	-0.554	-0.511	-0.637
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	-0.879	-1.296	-0.918	-0.176	-0.873	-1.223	-0.848	-2.383	-1.018
	δ_{AH}	-0.927	-1.210	-0.941	-0.212	-0.873	-1.219	-0.802	-2.392	-1.044
	t_{HAC}	-1.259	**-3.273**	**-2.091**	-0.349	**-2.209**	**-2.168**	**-2.123**	**-2.327**	**-1.837**
	t_{AH}	-1.642	**-3.215**	**-2.283**	-0.522	**-2.254**	**-2.429**	**-1.939**	**-2.779**	**-1.952**
TED_{t-1}	R^2	0.006	0.040	0.016	-0.003	0.017	0.020	0.013	0.027	0.011
	Corr(u,v)	-0.245	-0.075	-0.181	-0.208	-0.104	-0.161	-0.168	0.008	-0.206
Max(ρ_{uv}): 0.008		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}): -0.245	δ_{OLS}	-1.414	-0.982	-0.762	-0.402	-0.662	-0.239	-0.759	-0.880	-0.336
	δ_{AH}	-1.458	-0.982	-0.753	-0.439	-0.678	-0.220	-0.787	-0.880	-0.366
	t_{HAC}	**-3.125**	**-2.043**	-1.192	-0.435	-1.499	-0.513	-1.580	-1.160	-0.729
	t_{AH}	**-3.516**	**-2.589**	-1.318	-0.674	-1.522	-0.511	**-1.987**	-1.609	-1.130
	R^2	0.043	0.023	0.003	-0.003	0.005	-0.003	0.011	0.007	0.000
	Corr(u,v)	-0.160	-0.179	-0.130	-0.203	-0.124	-0.124	-0.189	-0.137	-0.230
$Term_{t-1}$		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy

	δ_{OLS}	0.345	0.393	0.773	0.115	0.517	0.459	0.436	0.562	0.299
Max(ρ_{uv}): 0.192	δ_{AH}	0.390	0.471	0.814	0.151	0.547	0.522	0.514	0.582	0.306
Min(ρ_{uv}): -0.057	t_{HAC}	0.806	1.090	**2.507**	0.375	**2.281**	1.282	1.515	0.982	0.712
	t_{AH}	1.033	**1.851**	**2.988**	0.559	**2.118**	1.551	**1.867**	1.001	0.853
	R^2	-0.001	0.005	0.029	-0.003	0.012	0.004	0.006	0.000	-0.001
	Corr(u,v)	0.121	0.049	0.151	0.179	0.077	0.138	0.123	0.051	-0.057
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	0.729	0.564	-0.191	0.006	0.185	0.078	0.559	0.589	0.468
	δ_{AH}	0.734	0.618	-0.125	0.071	0.199	0.121	0.592	0.663	0.487
	t_{HAC}	**2.834**	**2.074**	-0.388	0.014	0.696	0.261	**2.057**	**1.685**	**2.195**
	t_{AH}	**2.630**	**2.439**	-0.328	0.163	0.668	0.420	**2.248**	**1.822**	**2.277**
	R^2	0.024	0.016	-0.003	-0.004	-0.003	-0.004	0.015	0.007	0.016
	Corr(u,v)	0.041	0.163	0.140	0.161	0.024	0.065	0.143	0.192	0.098
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	-0.445	-0.351	-0.471	-0.328	-0.312	-0.332	-0.274	-0.636	-0.125
	δ_{AH}	-0.438	-0.364	-0.494	-0.334	-0.327	-0.353	-0.291	-0.647	-0.123
	t_{HAC}	**-2.471**	**-2.975**	**-3.052**	**-2.010**	**-2.476**	**-1.703**	**-1.955**	**-2.226**	-0.638
	t_{AH}	**-2.237**	**-2.749**	**-3.474**	**-2.386**	**-2.417**	**-2.005**	**-2.018**	**-2.138**	-0.655
$TB1y_t$	R^2	0.017	0.023	0.040	0.018	0.018	0.011	0.010	0.014	-0.002
	Corr(u,v)	0.043	-0.155	-0.213	-0.064	-0.148	-0.163	-0.175	-0.050	0.008
Max(ρ_{uv}): 0.043		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.233	δ_{OLS}	-0.487	-0.323	-0.252	-0.609	-0.184	-0.098	-0.379	-0.379	-0.232
	δ_{AH}	-0.504	-0.333	-0.258	-0.612	-0.188	-0.107	-0.403	-0.394	-0.233
	t_{HAC}	**-3.523**	**-2.119**	-1.137	**-2.611**	-1.302	-0.624	**-2.620**	**-2.152**	**-2.382**
	t_{AH}	**-3.477**	**-2.512**	-1.293	**-2.732**	-1.209	-0.714	**-2.935**	**-2.069**	**-2.074**
	R^2	0.041	0.020	0.002	0.026	0.002	-0.002	0.027	0.012	0.014
	Corr(u,v)	-0.161	-0.105	-0.045	-0.023	-0.036	-0.088	-0.233	-0.105	-0.008
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.340	0.156	0.088	0.168	-0.081	0.140	0.156	0.409	0.213
	δ_{AH}	0.344	0.142	0.092	0.174	-0.081	0.140	0.148	0.418	0.213
	t_{HAC}	**2.932**	**2.154**	0.970	**2.053**	-1.017	1.416	**1.734**	**2.556**	**1.877**
	t_{AH}	**2.773**	**1.682**	0.991	**1.936**	-0.930	1.244	1.606	**2.174**	**1.796**
wrd_{t-1}	R^2	0.027	0.009	0.000	0.011	-0.001	0.002	0.007	0.015	0.009
	Corr(u,v)	0.554	0.273	0.620	0.735	0.473	0.614	0.541	0.402	0.412
Max(ρ_{uv}): 0.861		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}): 0.273	δ_{OLS}	0.312	0.114	0.088	0.237	0.167	0.192	0.050	0.146	0.058
	δ_{AH}	0.319	0.115	0.087	0.240	0.169	0.190	0.055	0.148	0.063
	t_{HAC}	**3.146**	1.446	0.574	**1.659**	1.595	**1.816**	0.547	1.317	0.674
	t_{AH}	**3.459**	1.347	0.686	**1.669**	**1.716**	**1.997**	0.615	1.211	0.871
	R^2	0.042	0.003	-0.002	0.007	0.008	0.013	-0.003	0.002	-0.001
	Corr(u,v)	0.631	0.735	0.504	0.509	0.406	0.492	0.670	0.673	0.861
$Rg10fx_{t-1}$		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.032	-0.128	-0.184	-0.081	0.158	-0.061	0.161	-0.167	-0.227
Max(ρ_{uv}): 0.000	δ_{AH}	0.030	-0.136	-0.196	-0.082	0.138	-0.067	0.150	-0.176	-0.242
Min(ρ_{uv}): -0.396	t_{HAC}	0.140	-0.472	-1.046	-0.488	0.937	-0.263	0.832	-0.562	-0.805
	t_{AH}	0.126	-0.625	-1.045	-0.457	0.800	-0.299	0.770	-0.593	-0.988

	R^2	-0.005	-0.003	0.000	-0.004	-0.001	-0.005	-0.002	-0.003	-0.001
	Corr(u,v)	-0.175	-0.291	-0.300	-0.120	-0.343	-0.310	-0.312	-0.163	-0.188
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	-0.001	-0.006	-0.058	-0.136	0.126	0.086	0.060	-0.291	-0.109
	δ_{AH}	-0.009	-0.014	-0.068	-0.141	0.111	0.087	0.052	-0.297	-0.109
	t_{HAC}	-0.004	-0.040	-0.241	-0.568	0.531	0.340	0.327	-1.533	-0.848
	t_{AH}	-0.043	-0.088	-0.269	-0.606	0.503	0.411	0.304	-1.453	-0.788
	R^2	-0.005	-0.005	-0.005	-0.003	-0.003	-0.004	-0.004	0.005	-0.002
	Corr(u,v)	-0.316	-0.277	-0.197	-0.136	-0.243	-0.133	-0.396	-0.269	0.000
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	2.033	1.226	1.251	2.215	1.063	0.110	0.959	-1.060	-1.560
	δ_{AH}	1.907	1.167	1.284	2.139	1.216	0.024	0.942	-1.157	-1.485
	t_{HAC}	1.226	0.647	0.971	1.566	0.778	0.063	0.662	-0.384	-0.731
	t_{AH}	1.012	0.671	0.856	1.506	0.885	0.014	0.604	-0.487	-0.758
E$Term$_{t-1}$	R^2	0.001	-0.002	-0.002	0.007	-0.002	-0.005	-0.003	-0.004	-0.002
	Corr(u,v)	-0.182	-0.108	-0.114	-0.155	-0.131	-0.086	-0.171	-0.259	-0.107
Max(ρ_{uv}):-0.086		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.259	δ_{OLS}	0.221	1.785	0.518	-0.796	-2.235	-0.842	2.422	1.928	1.017
	δ_{AH}	0.149	1.743	0.522	-0.859	-2.183	-0.977	2.343	1.818	0.985
	t_{HAC}	0.160	1.575	0.256	-0.335	-1.457	-0.497	**1.798**	1.359	0.956
	t_{AH}	0.088	1.383	0.257	-0.461	-1.245	-0.579	**1.738**	1.112	0.894
	R^2	-0.005	0.005	-0.005	-0.004	0.003	-0.004	0.011	0.002	-0.001
	Corr(u,v)	-0.142	-0.243	-0.110	-0.178	-0.170	-0.139	-0.211	-0.192	-0.155
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.460	0.339	0.480	0.266	0.334	0.471	0.335	0.764	0.178
	δ_{AH}	0.477	0.345	0.478	0.278	0.333	0.474	0.338	0.744	0.181
	t_{HAC}	**2.541**	**2.769**	**3.493**	**1.751**	**2.883**	**2.457**	**3.237**	**2.987**	0.831
	t_{AH}	**2.582**	**2.270**	**3.450**	**2.107**	**2.526**	**2.787**	**2.324**	**2.608**	0.992
DivUS_E30_{t-1}$	R^2	0.020	0.016	0.042	0.012	0.021	0.026	0.017	0.024	0.000
	Corr(u,v)	0.105	0.045	0.131	0.115	0.050	0.114	0.111	-0.101	0.059
Max(ρ_{uv}): 0.136		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
Min(ρ_{uv}):-0.101	δ_{OLS}	0.506	0.416	0.197	0.450	0.078	0.053	0.432	0.460	0.264
	δ_{AH}	0.513	0.416	0.179	0.463	0.074	0.050	0.435	0.464	0.249
	t_{HAC}	**3.703**	**3.114**	0.973	**1.670**	0.562	0.325	**3.202**	**2.731**	**2.738**
	t_{AH}	**3.358**	**3.332**	0.916	**2.129**	0.472	0.336	**3.270**	**2.550**	**2.326**
	R^2	0.038	0.039	0.000	0.013	-0.003	-0.004	0.037	0.021	0.020
	Corr(u,v)	0.066	0.099	0.020	0.119	0.049	0.035	0.136	0.108	0.019
		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.019	0.005	0.019	0.007	0.013	0.014	0.016	0.033	0.014
	δ_{AH}	0.019	0.005	0.020	0.007	0.014	0.015	0.016	0.033	0.014
MonP_US$_{t-1}$	t_{HAC}	**2.391**	0.797	**3.252**	1.178	**2.262**	**1.928**	**2.472**	**2.842**	1.530
	t_{AH}	**2.248**	0.777	**3.110**	1.160	**2.170**	**1.874**	**2.364**	**2.559**	1.625
Max(ρ_{uv}): 0.122	R^2	0.012	-0.001	0.026	0.001	0.011	0.007	0.014	0.017	0.004
Min(ρ_{uv}): -0.048	Corr(u,v)	0.033	0.025	0.032	0.122	0.016	0.037	0.053	0.004	0.007
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	0.028	0.019	0.005	0.025	0.008	0.010	0.019	0.024	0.013
	δ_{AH}	0.029	0.020	0.004	0.026	0.008	0.010	0.020	0.024	0.014

	t_{HAC}	**3.958**	**3.562**	0.540	**2.204**	1.100	1.411	**3.367**	**2.869**	**3.013**
	t_{AH}	**3.920**	**3.414**	0.488	**2.655**	1.136	1.357	**3.197**	**2.932**	**2.795**
	R^2	0.042	0.031	-0.002	0.018	0.001	0.002	0.028	0.023	0.020
	Corr(u,v)	0.070	0.072	-0.048	0.072	-0.010	0.114	0.050	0.046	0.100
$E\$30_t$ Max(ρ_{uv}): 0.055 Min(ρ_{uv}):-0.142		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	-0.201	-0.118	-0.217	-0.139	-0.076	-0.192	-0.174	-0.188	-0.066
	δ_{AH}	-0.197	-0.126	-0.225	-0.133	-0.081	-0.191	-0.179	-0.182	-0.067
	t_{HAC}	**-1.682**	-1.268	**-2.088**	-1.189	-0.951	-1.438	**-2.229**	-1.076	-0.492
	t_{AH}	**-1.763**	-1.212	**-2.512**	-1.438	-0.932	**-1.796**	**-1.828**	-1.187	-0.535
	R^2	0.007	0.001	0.015	0.004	-0.001	0.007	0.007	0.002	-0.002
	Corr(u,v)	0.049	-0.073	-0.142	0.055	-0.037	-0.012	-0.071	0.012	-0.010
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	-0.076	-0.175	-0.087	-0.133	-0.101	-0.038	-0.250	-0.131	-0.121
	δ_{AH}	-0.089	-0.179	-0.086	-0.114	-0.103	-0.041	-0.262	-0.131	-0.121
	t_{HAC}	-0.778	**-2.032**	-0.582	-0.895	-1.059	-0.343	**-2.665**	-1.523	**-1.769**
	t_{AH}	-0.819	**-2.210**	-0.697	-0.882	-0.923	-0.356	**-3.064**	-1.327	**-1.709**
	R^2	-0.002	0.011	-0.002	0.000	-0.001	-0.003	0.023	0.002	0.006
	Corr(u,v)	-0.019	-0.065	-0.034	0.037	0.005	-0.045	-0.133	-0.013	0.012
BondYield$_{t-1}$ Max(ρ_{uv}): 0.254 Min(ρ_{uv}):-0.058		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	1.370	1.565	1.644	0.959	0.724	1.446	1.530	1.727	1.655
	δ_{AH}	1.364	1.561	1.657	0.987	0.741	1.458	1.543	1.706	1.662
	t_{HAC}	**2.575**	**3.830**	**4.166**	**2.581**	**1.918**	**2.829**	**4.129**	**1.985**	**2.934**
	t_{AH}	**3.037**	**4.079**	**4.687**	**2.752**	**2.099**	**3.495**	**3.907**	**2.467**	**3.536**
	R^2	0.018	0.034	0.044	0.014	0.007	0.024	0.031	0.012	0.025
	Corr(u,v)	-0.023	0.026	0.116	0.176	0.143	0.084	0.102	-0.058	0.042
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	1.308	1.347	0.571	1.249	0.929	1.238	1.547	1.087	1.046
	δ_{AH}	1.316	1.362	0.566	1.249	0.937	1.239	1.572	1.111	1.075
	t_{HAC}	**2.957**	**4.281**	0.818	**1.978**	**1.772**	**2.571**	**4.297**	**2.716**	**3.723**
	t_{AH}	**3.159**	**4.015**	1.142	**2.268**	**2.241**	**2.804**	**4.598**	**2.623**	**3.771**
	R^2	0.020	0.032	0.001	0.009	0.009	0.015	0.042	0.012	0.027
	Corr(u,v)	0.057	0.132	0.009	0.025	0.048	0.052	0.190	0.154	0.254
Cay$_{t-1}$ Max(ρ_{uv}):-0.215 Min(ρ_{uv}):-0.533		Australia	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy
	δ_{OLS}	0.963	0.500	0.881	0.344	0.128	1.115	1.237	1.337	0.458
	δ_{AH}	0.879	0.426	0.783	0.213	0.063	0.980	1.129	1.134	0.343
	t_{HAC}	**1.831**	0.658	1.495	0.640	0.196	1.602	**2.094**	1.155	0.683
	t_{AH}	1.324	0.655	1.261	0.388	0.113	1.383	**1.720**	1.021	0.427
	R^2	0.007	-0.003	0.007	-0.004	-0.006	0.010	0.017	0.003	-0.005
	Corr(u,v)	-0.260	-0.248	-0.286	-0.408	-0.248	-0.340	-0.316	-0.320	-0.264
		Japan	Netherlands	Norway	Singapore	Spain	Sweden	Switzerland	UK	USA
	δ_{OLS}	0.056	1.410	-0.038	0.471	0.540	0.686	1.529	1.657	1.545
	δ_{AH}	-0.077	1.305	-0.116	0.311	0.410	0.547	1.414	1.539	1.403
	t_{HAC}	0.074	**3.094**	-0.039	0.504	0.944	1.007	**2.927**	**3.051**	**3.752**
	t_{AH}	-0.108	**2.376**	-0.135	0.312	0.552	0.767	**2.464**	**2.331**	**3.054**
	R^2	-0.007	0.037	-0.007	-0.005	-0.003	-0.001	0.040	0.035	0.066
	Corr(u,v)	-0.309	-0.332	-0.215	-0.310	-0.324	-0.375	-0.351	-0.322	-0.533