

**A Partial Explanation for Post-Earnings-Announcement Drift:
Autocorrelation Risk in Earnings**

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ABSTRACT

I examine autocorrelation risk in earnings as a partial explanation for post-earnings-announcement drift. Autocorrelation risk refers to systematic temporal variation in the autocorrelation of seasonally-differenced earnings (SDE). Rational investors should impound earnings information into price as if they adjust autocorrelation coefficients to certainty equivalents to reflect any systematic temporal variation in SDE autocorrelation. The use of certainty-equivalent-adjusted autocorrelation coefficients could produce drift in future returns related to current SDE and the appearance of biased autocorrelation coefficients impounded into price. This is important because it provides one possible explanation for the results in Ball and Bartov [1996]. I provide evidence that SDE autocorrelation varies with future economic growth, contains systematic temporal variation shared by sample firms, and varies with a proxy for investors' intertemporal marginal rate of substitution for consumption. Analysis of returns suggests that 20% to 25% of the average returns associated with the SDE strategy arise from autocorrelation risk.

I. INTRODUCTION

This study develops and tests a risk-based explanation for post-earnings-announcement drift returns. Drift remains one of the most puzzling anomalies in accounting research, defying explanation since it was first observed by Ball and Brown [1968]. The anomalous nature of the phenomenon leads many researchers to accept the possibility that even highly competitive capital markets do not price all the information in quarterly earnings with full efficiency. In this paper I continue the search for an explanation by drawing on asset pricing theory to model and predict that autocorrelation of quarterly seasonally-differenced earnings (SDE) itself possesses risk and explains a portion of the post-earnings-announcement drift anomaly. The results suggest that autocorrelation in quarterly SDE reflects systematic temporal variation that explains 20-25% of the returns to the drift strategy.

Post-earnings-announcement drift puzzles researchers because stale earnings numbers should not predict future returns in a market that uses earnings information quickly, completely, and in an unbiased manner. The most widely-accepted explanation for this anomaly links drift to the time-series properties of earnings. Autocorrelation coefficients summarize the implications of current and prior quarters' SDE for next quarter SDE. Prior research links post-earnings-announcement drift to evidence that the market impounds seemingly-biased earnings autocorrelation coefficients into share price (Rendleman, Jones and Latane [1987], Bernard and Thomas [1990], Ball and Bartov [1996], Collins and Hribar [2001]). The bias in the autocorrelation coefficients impounded in price could reflect the naïve use of earnings information by stock market participants. For example, the prevailing explanation of the anomalous returns suggests that the market naïvely undervalues the implications of current positive SDE and naïvely overvalues the implications of current negative SDE.

The drift phenomenon persists despite the conclusion by many researchers that it arises from inefficient use of earnings information (Doyle, Lundholm, and Soliman [2003], Nichols and Wahlen [2004]). For some researchers, intuition suggests that any *true* inefficiency as well-documented and widely-known as post-earnings-announcement drift should not survive in U.S. capital markets – highly competitive markets characterized by enormous incentives to efficiently use all available information (Jacob, Lys, and Sabino [2000]). The persistence of drift more than 35 years after Ball and Brown [1968] suggests a complex phenomenon that likely arises from multiple sources, including mispricing, trading frictions (Bhushan [1994], Sadka and Sadka [2004]), and risk (Chordia and Shivakumar [2001, 2002]).

In this paper, I examine the contribution of risk to post-earnings-announcement drift. I rely on asset pricing theory to develop a model of expected returns based on rational, expected-utility maximizing behavior by investors that is consistent with two important features of the drift evidence: (1) the model predicts that a systematic relation exists between current SDE and future returns; and (2) the model predicts that the market *rationally* impounds seemingly-biased autocorrelation coefficients into price. This is the first risk-based explanation to address these crucial results from prior literature.

These predictions arise by relaxing an implicit assumption maintained by prior research. The papers linking drift to the apparent inefficient use of earnings information assume that firms' SDE autocorrelation coefficients do not vary over time in any systematic fashion. The validity of this assumption is important, and is the subject of this paper. I show that temporal variation in SDE autocorrelation that is common (i.e., systematic) across firms should, in theory, produce patterns in stock returns similar to those observed in prior drift studies. In particular, systematic temporal variation in SDE autocorrelation, or 'autocorrelation risk,' can lead investors to

impound earnings information into price as if they adjust autocorrelation coefficients to certainty equivalents. Certainty-equivalent-adjusted autocorrelation coefficients impounded in price can produce a relation between current SDE and future returns consistent with the drift. The model demonstrates that the *sign and magnitude* of the risk adjustment in returns associated with autocorrelation risk is directly related to the *sign and magnitude* of current period SDE – the very partitioning variable used by prior studies to document the drift anomaly.

The basic intuition for autocorrelation risk is that autocorrelation in earnings is a function of future business conditions, and so are investors' consumption decisions. To understand how autocorrelation risk can lead investors to seemingly undervalue the implications of current positive SDE and overvalue the implications of current negative SDE, first consider what autocorrelation coefficients represent. The autocorrelation from an earnings regression is the relation between current SDE and the expected value of future SDE. The autocorrelation impounded in price, on the other hand, is the relation between current SDE and the *value to the investor* of future SDE. The autocorrelation risk model in this paper shows that the expected value of future SDE from an autoregression is not necessarily equivalent to the market's expected value of future SDE, creating the appearance that share prices impound biased autocorrelation coefficients.

The relations that would lead the market to impound seemingly-biased autocorrelation coefficients into price are precisely the relations that would hold if (a) autocorrelation positively varies with consumption (or, equivalently, negatively varies with marginal utility for consumption), and (b) market share prices are formed by risk-averse investors who prefer smooth consumption across states and over time. Under these conditions, high positive SDE leads to larger future earnings increases when future consumption is high, but smaller earnings

increases when future consumption is low. Because the marginal utility of additional earnings to a risk-averse investor is low when consumption is high (and high when consumption is low), the investor values the future positive SDE at a discount relative to its expected value. On the other hand, negative current SDE leads to larger earnings declines when future consumption is high, but smaller earnings declines when future consumption is low. Because the asset with negative current SDE performs better when times are bad than when times are good, the investor will place a greater value on this asset's future SDE than suggested by its expected value.

In the empirical analysis, I conduct three sets of tests of the implicit assumption in prior work that autocorrelation reflects no systematic variation. First, I examine the association between autocorrelation and unexpected future GDP growth. This analysis examines whether variation in autocorrelation is associated with uncertainty about future economic conditions that likely matter to investors' consumption decisions, such as the general health of the economy. Second, I directly examine whether systematic temporal variation exists in autocorrelation by examining the association between autocorrelation and an autocorrelation index that reflects aggregate temporal variation in SDE autocorrelation. Third, I examine whether autocorrelation negatively varies with investors' intertemporal marginal rate of substitution for consumption (IMRS or pricing kernel).¹ Generally, the results indicate that the maintained assumption does not hold – autocorrelation positively varies with unexpected future GDP growth, reflects systematic temporal variation, and negatively co-varies with the pricing kernel.

Not only is the maintained assumption violated, but the variation in SDE autocorrelation is consistent with autocorrelation as a contributing source of drift. This leads to the second

¹ IMRS is the ratio of next period marginal utility for consumption (discounted for time) to current marginal utility for consumption. Negative covariation with the pricing kernel implies positive covariation with consumption. A central conclusion of asset pricing theory holds that all fundamental risk arises from the covariance between asset payoffs and investor IMRS. For example, under the assumptions of the CAPM, the market portfolio is perfectly correlated with investor IMRS. See Cochrane [2001] for an excellent discussion of current asset pricing theory.

objective of the empirical analysis, which assesses the implications of autocorrelation risk for the anomalous post-earnings-announcement drift returns. I examine whether the appropriate risk adjustment depends on current SDE for both firm-specific and SDE decile portfolio returns. I also assess the adequacy of size-adjusting returns to control for autocorrelation risk, and I examine the risk inherent in returns to a hedge portfolio based on SDE.

I find that the risk premium reflected in returns depends on current SDE in both firm-specific and SDE decile portfolio regressions, as predicted by the autocorrelation risk model. Furthermore, I find that the pricing kernel conditioned on SDE explains an economically-significant portion of the temporal variation in hedge portfolio returns; a one-standard-deviation increase in the pricing kernel corresponds to a 50% reduction in the returns to hedge portfolios formed on extreme SDE. Finally, the pricing kernel I use in this paper suggests that approximately 20-25% of the average returns to the SDE strategy reflect compensation for risk.

Recent research confirms that post-earnings-announcement drift continues to survive more than 35 years after Ball and Brown [1968] first documented the phenomenon.² As pointed out by Jacob, Lys, and Sabino [2002], in a highly competitive market arbitragers should eliminate inefficiencies, especially once the inefficiencies become widely known. The persistence of drift points to a more complex, less easily arbitrated cause than investor naïveté. This paper identifies and provides evidence consistent with one such possible contributing source of drift.

The next section discusses the relevant evidence on post-earnings-announcement drift. Section III presents a model in which earnings autocorrelation varies with investor marginal utility. This section demonstrates that the autocorrelation implied by stock prices can differ from

² Doyle, Lundholm, and Soliman [2003] and Nichols and Wahlen [2004] document the continued existence of drift using data from 1988 to 2000 and 1988 to 2002, respectively.

the autocorrelation estimated from earnings data if autocorrelation varies with the pricing kernel. Section IV describes the sample selection and variable measurement. Sections V and VI present the results for the earnings-based and returns-based tests, respectively. Section VI concludes.

II. BACKGROUND

This paper seeks to provide a better understanding of the contribution of risk to post-earnings-announcement drift. The inability of previous risk-based theories to explain two key pieces of the drift evidence leads many accounting scholars to conclude that post-earnings-announcement drift represents evidence of some degree of market inefficiency with respect to earnings information. First, returns continue in the same direction as the sign of the most recent SDE in the period after the earnings announcement. In an efficient market, prices respond to new information quickly, completely, and in an unbiased manner. Thus, no systematic association should exist between stale information and future returns.

Second, current SDE predicts the relative magnitude and sign of returns surrounding future earnings announcements. Current SDE carries implications for the next four quarters' SDE. The magnitude of these implications, as summarized by autocorrelation coefficients, decrease over the first three subsequent quarters and reverse (become negative) for the fourth quarter. The announcement period abnormal returns over these quarters exhibit a similar pattern: decreasing magnitude over the first three quarters followed by a reversal in the fourth. The ability to predict the relative magnitude and sign of announcement period returns imposes 'strain' on risk-based stories (Bernard, Thomas, and Wahlen [1997 96] (BTW)). The 'strain on a risk-based explanation is compounded' when, for the same portfolio, returns are predictably positive for some earnings announcement periods but predictably negative for others (BTW).

These two aspects of the evidence on drift pose the greatest challenge to risk-based explanations. Accounting research offers an explanation for this evidence based on market inefficiency, which I label the ‘naïve mispricing hypothesis.’ The naïve mispricing hypothesis posits that prices reflect the expectations of investors who do not understand the earnings-generating process. In particular, prices behave as if at least some investors believe earnings follow a random walk in seasonal differences when a seasonally-differenced autoregressive model better approximates the ‘true’ earnings-generating process.³ Such naïve beliefs lead investors to underreact to current SDE, causing drift.⁴ Investors learn of their biased expectations upon announcement of next quarter’s earnings. Returns concentrate during these periods as investors correct their erroneous expectations. The sign and relative magnitude of earnings announcement period returns correspond to the sign and relative magnitude of forecast errors from a naïve expectations model.⁵

The naïve mispricing hypothesis serves as the most widely accepted explanation for drift because it can explain both aspects of the anomalous evidence. However, asset pricing research provides an alternative perspective on the appropriate interpretation of returns concentration around earnings announcements. Papers as early as Robichek and Myers [1966] and Epstein and Turnbull [1980] predict that risk premia will concentrate around significant information events. Chari, Jagannathan, and Ofer [1988], Ball and Kothari [1991] and recent papers by Chambers, Jennings, and Thomson [2003] and Cohen, Dey, Lys, and Sunder [2003] support

³ Bernard and Thomas [1990] point out that the AR(1) model in seasonal differences augmented with a fourth-order forecast error from the Foster [1977] model approximates the slightly better-fitting Brown-Rozeff [1979] model.

⁴ It is not clear why investors hold this naïve belief in the first place.

⁵ Jacob, Lys, and Sabino [2000] document that forecast errors from the Foster model display the familiar (+,+,+,-) pattern, especially when researchers over-difference a stationary series. This creates ambiguity in interpreting the evidence in Bernard and Thomas [1990], because the market’s forecast errors are consistent with the use of both a naïve seasonal random walk model and the more sophisticated Foster model.

these predictions with empirical evidence.⁶ Return concentration per se does not help distinguish between mispricing and risk.⁷ Rather, the sign pattern of future returns remains as arguably the most difficult hurdle for risk-based explanations (Bernard, Thomas, and Wahlen [1997]).

Other evidence seems difficult to reconcile with the naïve mispricing view. Ball and Bartov [1996] document that prices act as if investors understand the structure of the time-series process governing earnings, but underestimate the parameters of this process.⁸ Ball and Bartov [1996 331] summarize the conditions that must hold for naïve mispricing to explain this result. Investors must be: “(1) aware of random walks in earnings; (2) aware of seasonals in earnings; (3) aware of both the existence and the (+,+,+,-) sign pattern of the correlation in seasonally-differenced earnings across adjacent calendar quarters; but (4) unaware that they systematically underestimate the correlation.” After thoroughly discussing each of these conditions, Ball and Bartov [1996] note that the complexity of the expectational errors seems inconsistent with the naïve use of information, as proposed by the naïve investor hypothesis. Ball and Bartov [1996 335] conclude: “In our view, the evidence remains anomalous, that is difficult to reconcile with *any* refutable theory” (emphasis added).

Mendenhall [2002] provides evidence similar in spirit to Ball and Bartov [1996]. Mendenhall [2002] finds that historical, firm-specific autocorrelation in SDE predicts future, firm-specific autocorrelation in SDE. Moreover, Mendenhall [2002] finds that investors seem to impound cross-firm differences in historical autocorrelation into price, but seem to systematically understate the historical autocorrelation. The complexity of expectations

⁶ Moreover, the sign of the return concentration at earnings announcements should correspond to the sign of the risk adjustment. If the risk adjustment is negative, consistent with a hedge in consumption volatility, the return concentration at earnings announcements would be negative.

⁷ This is contrary to Ali, Hwang, and Trombley [2003], who rely on return concentration around earnings announcements to conclude that Frankel and Lee’s [1998] value-to-price strategy is mispricing instead of risk.

⁸ Ball and Bartov [1996] examine expectations in stock prices two days before the subsequent earnings announcement. This likely overstates the market’s implicit autocorrelation relative to when the market first updates expectations after learning prior period earnings, as pointed out by Soffer and Lys [1999].

documented by Ball and Bartov [1996] and Mendenhall [2002] seems difficult to reconcile with the naïve mispricing view. For example, it is not clear how investors are sufficiently sophisticated to understand the general process mapping lagged earnings changes into future earnings changes, are sufficiently sophisticated to understand that such mapping varies across firms, yet are not sufficiently sophisticated to estimate the magnitude of those relations in an unbiased manner.⁹

The autocorrelation risk model in the next section provides an explanation to fit the Ball and Bartov [1996] and Mendenhall [2002] evidence. In particular, autocorrelation coefficients implied by stock prices will differ from those estimated from earnings data if autocorrelation co-varies with the pricing kernel. Such a difference between the autocorrelation in earnings and that impounded in price produces a systematic relation between current SDE and future returns. This model proposes that market prices efficiently impound the information in earnings. Thus, the complexity of expectations impounded in stock price mirrors the complexity in the earnings-generating process. However, investors rationally use seemingly-biased parameters because of the risk inherent in that earnings-generating process.

III. A MODEL OF AUTOCORRELATION RISK

I summarize here the three basic assumptions I invoke to develop the autocorrelation risk model. For additional details on the model development, please see Appendix B. First, I assume no arbitrage, which holds that investors cannot create portfolios with strictly positive expected returns but that will certainly never cost anything (i.e., no initial investment and no chance of

⁹ Bartov, Radhakrishnan, and Krisky [2000] provide one possible explanation that reconciles the naïve mispricing view with the finding that the market places a nonzero weight on current and past SDE. In particular, they suggest that informed traders also influence price, and that the weight placed on SDE in equilibrium should be an increasing function of institutional ownership. Their results and my results are not mutually exclusive.

loss in the future). No arbitrage represents the minimum characterization of investor preferences to ensure that an equilibrium exists in capital markets (Harrison and Kreps [1979], Rubinstein [1976], Cochrane [2001], Christensen and Feltham [2003]). Second, I assume unexpected returns respond to unexpected earnings information. This assumption is firmly rooted in accounting theory (e.g., Ohlson [1995], expression (6), Christensen and Feltham [2003]) and is supported by ample empirical evidence (e.g., Foster [1977]). This assumption is important because it connects returns to earnings information, thereby connecting the risk in returns to the risk in earnings.¹⁰ The third assumption, which is the primary focus of this paper, holds that temporal (more precisely, event-contingent) variation exists in the autocorrelation structure of earnings. These three assumptions imply the following model of expected returns (see Appendix B for additional details):

$$E(R_{t,t+1}) = R_{t,t+1}^f \left[1 - \phi_1 \text{cov}(m_{t,t+1}, b_{t+1}) SDE_t - \phi_1 \text{cov}(m_{t,t+1}, e_{t+1}) - \text{cov}(m_{t,t+1}, v_{t,t+1}) \right] \quad (1)$$

where $R_{t,t+1}$ is the gross return on a risky asset for the period from t to $t+1$,

$R_{t,t+1}^f$ is the gross return on the riskless asset for the same period,

$m_{t,t+1} = \frac{\beta u'(c_{t+1})}{u'(c_t)}$ is the pricing kernel ($u'(c_t)$ is marginal utility for consumption at time

t , and β denotes the investor's time preference for consumption),

SDE_t denotes the seasonal change in quarterly earnings (scaled by price),

b_{t+1} and e_{t+1} are the random autocorrelation and error from the following model of SDE:

$$SDE_{t+1} = b_{t+1} SDE_t + e_{t+1},$$

¹⁰ Alternatively, one can assume clean surplus accounting. Feltham and Ohlson [1999] demonstrate that the fundamental risk reflected in dividends is the same as the fundamental risk in earnings and book values under the assumptions of no arbitrage and clean surplus accounting.

ϕ_1 and $v_{t,t+1}$ are the earnings response coefficient and random error from the following

$$\text{model of returns and unexpected earnings (UE): } R_{t,t+1} = E(R_{t,t+1}) + \phi_1 UE_{t+1} + v_{t,t+1}.$$

The covariance terms on the right-hand side represent the risk inherent in returns implied by the three assumptions described above. Note that all random variables have a corresponding covariance term with the pricing kernel. Any non-zero covariance would be a part of the risk adjustment. I label the covariance between b_{t+1} and $m_{t,t+1}$ ‘autocorrelation risk.’

The key insight from expression (1) is that *the risk adjustment depends on the sign and magnitude of current SDE* if autocorrelation varies with the pricing kernel. Suppose that $cov(m_{t,t+1}, v_{t,t+1})$ and $cov(m_{t,t+1}, e_{t+1})$ are not systematically related to SDE_t , but are related to other conventional risk measures, such as size. The use of size-adjusted returns in examining the performance of extreme SDE_t portfolios will adequately control for these elements of risk.¹¹ However, the autocorrelation risk adjustment in size-decile returns will be based on the average SDE for the firms in that portfolio. If size is not related to SDE, size-based portfolios will likely have an average level of SDE and thus will not control for autocorrelation risk in SDE-sorted portfolios. This suggests that using size-adjusted returns does not control for autocorrelation risk in extreme SDE_t deciles.

In addition, after controlling for other elements of risk, the covariance between *returns and the pricing kernel* should be *negative* for high SDE_t firms but *positive* for low SDE_t firms. This is because, after controlling for the risk in $cov(m_{t,t+1}, v_{t,t+1})$ and $cov(m_{t,t+1}, e_{t+1})$, the risk in returns is given by the following expression: $cov(m_{t,t+1}, R_{t,t+1}) = \phi_1 cov(m_{t,t+1}, b_{t+1}) SDE_t$. As the sign of SDE_t changes, so does the sign of the covariance between returns and the pricing kernel.

¹¹ Use of size-adjusted returns was adopted by Rendleman, Jones, and Latane [1982] and has been the standard method for risk control in drift studies since.

To highlight the risk in hedge portfolio returns implied by the autocorrelation risk model, consider the following extension of (1):

$$E(HedgeRet_{t,t+1}) = -R_{t,t+1}^f \phi_1 \text{cov}(m_{t,t+1}, b_{t+1}) (SDE_t^+ - SDE_t^-) \quad (1a)$$

where $HedgeRet_{t,t+1}$ denotes the hedge portfolio return for the period from t to $t+1$, and SDE_t^+ (SDE_t^-) denotes the average SDE for firms in the most extreme positive (negative) SDE decile. In this expression, I make the simplifying assumption that SDE is the only difference across firms in the extremes of the SDE distribution. As a result, all the other terms from (1) cancel out. As expression (1a) reveals, if $\text{cov}(m_{t,t+1}, b_{t+1}) = 0$ then the expected returns to the hedge portfolio equal zero. Returns to hedge portfolios will be positive if autocorrelation negatively varies with the pricing kernel. Moreover, the hedge portfolios formed on SDE scale $\text{cov}(m_{t,t+1}, b_{t+1})$ by the *spread* in SDE across the extreme portfolios. SDE-sorted hedge portfolios tend to maximize the exposure to autocorrelation risk.

The three basic assumptions also imply the following expression for realized returns:

$$R_{t,t+1} = R_{t,t+1}^f + \phi_1 \left(SDE_{t+1} - [E(b) + R_{t,t+1}^f \text{cov}(m_{t,t+1}, b_{t+1})] SDE_t \right) + \Phi_{t,t+1} \quad (2)$$

where $\Phi_{t,t+1} = v_{t,t+1} - R_{t,t+1}^f \text{cov}(m_{t,t+1}, v_{t,t+1}) - R_{t,t+1}^f \phi_1 \text{cov}(m_{t,t+1}, e_{t+1})$. The model in (2) resembles the non-linear least squares model used by Collins and Hribar [2001] and Kimbrough [2001] and is similar in spirit to the OLS approach used by Ball and Bartov [1996] and Mendenhall [2002]. The key insight from expression (2) is that the weight on current SDE in a returns-based regression equals $E(b) + R_{t,t+1}^f \text{cov}(m_{t,t+1}, b_{t+1})$ and will rationally differ from the weight given to it in an earnings regression if autocorrelation co-varies with the pricing kernel. If the covariance is zero, then autocorrelation is not ‘risky’ and autocorrelation risk cannot contribute to drift. The

apparent inefficient use of SDE information documented in prior drift studies is consistent with *negative* covariance between autocorrelation and the pricing kernel.

In appendix B, I expand the model to also consider the autocorrelation for the fourth lag. This is important because, as mentioned previously, much of the troubling evidence regarding post-earnings announcement drift relates to the reversal of sign in the autocorrelation for the fourth lag. I do not present that model in this section because the model itself does not provide new insight into autocorrelation risk, but instead is merely an extension of the model discussed above.¹²

The autocorrelation risk model developed in this section demonstrates that post-earnings-announcement drift could be consistent with a rational explanation if autocorrelation varies with investors' IMRS. As pointed out earlier, prior literature on drift implicitly assumes that no systematic variation exists in the autocorrelation structure of SDE. The empirical analysis assesses the descriptive validity of this assumption and the consequences for drift if this assumption does not hold.

IV. SAMPLE SELECTION AND VARIABLE MEASUREMENT

In this section, I first describe the sample selection and the definitions of earnings and returns used in the analysis. Then, I introduce the pricing kernel I use in this paper.

Sample Selection, Earnings, and Returns

The sample draws firm-quarters from the intersection of Compustat and CRSP data files. In particular, I access Compustat data from the current and first two backdata files for the quarterly industrial, full coverage, and research files. The primary earnings variable is SDE.

¹² Appendix B calibrates the autocorrelation risk model using the data in my sample and demonstrates the magnitude of the covariance between autocorrelation and the pricing kernel must be in order to fully explain drift in my sample.

Several alternative methods of computing SDE have appeared in the literature with seemingly little difference in results across methods. I compute SDE as the seasonal change in earnings (defined as operating income after depreciation) for the current quarter scaled by the firm's time-series standard deviation of seasonal earnings changes for the prior eight quarters.¹³ This measure promotes the comparison of my results with the results from prior research. In addition, Chordia and Shivakumar [2001 4] argue that deflating by market value could induce a relation between earnings and future macroeconomic variables, such as GDP growth.¹⁴ I use monthly returns from CRSP. For some analyses, I use quarterly returns, defined as monthly returns compounded from the month after the earnings announcement for quarter t to the month that includes the announcement of quarter $t+1$ earnings. The sample includes 117,614 firm-quarter observations from 1975:3 to 2002:12.

Sample descriptive statistics

Table 1 reports descriptive statistics for my sample. The median firm generated \$6.2 million dollars in operating income after depreciation. The median seasonal earnings change is \$0.44 million, while the median SDE is 0.32. The median firm is relatively small, with a market capitalization of \$218 million, while the mean market capitalization is \$1.86 billion.

Replication of post-earnings-announcement drift

Table 2 reports the replication of post-earnings-announcement drift with my sample. Panel A reports the results from estimating Fama-MacBeth regressions of quarterly cumulative returns on quarterly SDE decile rank, scaled to the interval (0,1). The table reports the average coefficient from 110 quarterly cross-sectional regressions. Inferences are based on the

¹³ Chordia and Shivakumar [2001, 2002] and Sadka and Sadka [2003] use a similar scaling method for SDE.

¹⁴ Inferences are generally unchanged when I scale seasonal earnings changes by market value of equity at the beginning of the return cumulation period. The main exception is for the GDP growth analysis, where the interaction between lagged SDE and unexpected GDP growth reported in Table 4 is significantly negative for most intervals examined.

distribution of the coefficient estimates. Consistent with prior drift literature, the first (fourth) lag possesses significantly positive (negative) predictive power for future returns. While the third lag is significant, its sign is inconsistent with prior literature and its magnitude is well below the magnitude of the first and fourth lags.

I link drift to biased autocorrelation coefficients impounded in prices by nonlinear least squares estimation of the following system of equations:

$$\begin{aligned} SDE_{t+1} &= a + b_1 SDE_t + b_2 SDE_{t-1} + b_3 SDE_{t-2} + b_4 SDE_{t-3} + e_{t+1} \\ CR_{t,t+1} &= \phi_0 + \phi_1 [SDE_{t+1} - (a + b'_1 SDE_t + b'_2 SDE_{t-1} + b'_3 SDE_{t-2} + b'_4 SDE_{t-3})] + \gamma_{t,t+1} \end{aligned} \quad (3)$$

where CR denotes the cumulative raw return.¹⁵ Coefficients from the earnings regression are similar to results from prior research. In particular, the coefficients exhibit the declining magnitude across the first three lags and the reversal in the fourth lag. Coefficients from the returns equation exhibit evidence of biased expectations for the first and fourth lags only. These results are generally consistent with Panel A and with prior research that finds that the bias in expectations is most severe for the first and fourth lags.

The pricing kernel

An integral feature of my research design is the pricing kernel that I employ. Asset pricing theory predicts that investors' intertemporal marginal rate of substitution for consumption (IMRS or pricing kernel) exactly prices all assets in equilibrium. Empirically, estimating investors' IMRS is a nontrivial challenge. Factor pricing models represent the most common approach to empirically specifying the pricing kernel (Cochrane [2001]). For example, the CAPM measures risk by reference to the market portfolio because the underlying assumptions of the CAPM imply that the market portfolio perfectly correlates with investors' IMRS. Unfortunately, asset pricing research has not developed a cohesive body of evidence that

¹⁵ Results change very little when using size-adjusted returns.

unambiguously identifies the factors that should appear in the model. In fact, Chordia and Shivakumar [2001, 2002] even advocate using hedge portfolio returns from a SDE-based trading strategy as a factor.

In response to the inconclusiveness of factor pricing model research, another branch of asset pricing research is developing an alternative approach (e.g., Chen and Knez [1996], Ahn, Conrad, and Dittmar [2003]). In this literature, the researcher imposes the minimum conditions for equilibrium to exist in capital markets and specifies reference assets that attempt to span the investment opportunity set (IOS) available to investors in equilibrium. Then, the researcher examines whether trading strategies significantly expand investors' IOS. If the researcher finds that the trading strategy does not expand the IOS, this suggests that the assets in the trading strategy are correctly priced. On the other hand, if the researcher finds that the trading strategy does expand the IOS available to investors, this is evidence that the trading strategy is not rationally priced in equilibrium.

I adopt this approach to extract an empirical proxy for the pricing kernel from market data. First, I assume that the law of one price holds. The law of one price states that two assets that have identical payoffs across all possible future contingent events have identical prices.¹⁶ The law of one price is a weak characterization of investor preferences and is sufficient to ensure that a pricing kernel exists that prices all assets in equilibrium (see Cochrane [2001] for a proof). Next, I select a set of reference assets. Imposing the law of one price on a set of reference assets provides a pricing kernel that prices all the *reference assets* exactly (see Appendix C for details on extracting the pricing kernel). Because the pricing kernel prices the reference assets exactly I use it as my proxy for investors' IMRS, which, in theory, should price *all assets* exactly.

¹⁶ This is a weaker assumption than no arbitrage, which I assumed in the development of the autocorrelation risk model.

Note that this approach shifts the focus from specifying an appropriate factor pricing model to specifying an appropriate set of reference assets (Chen and Knez [1996]). If the reference assets do reasonably well in spanning the IOS, then the extracted pricing kernel will do reasonably well in empirical applications.¹⁷ I sort all monthly returns from CRSP for the 1975 to 2002 period into twenty industry portfolios, which I use as the reference assets.¹⁸ I take into account two considerations in this choice of reference assets. First, if the reference assets are to span the IOS available to investors, the reference assets should be chosen to maximize within-group correlation and minimize cross-group correlation (Ahn, Conrad, and Dittmar [2003]). In this way, each reference asset adds to the IOS over and above what the other reference assets contribute. Second, the choice of reference assets should not be associated with the post-earnings-announcement drift phenomenon. King [1966] demonstrates that industry-sorted portfolios fulfill the first requirement, while Doyle, Lundholm, and Soliman [2003] demonstrate that drift is not concentrated in any particular industry.

Chen and Knez [1996] identify a two step procedure for testing if a trading strategy significantly enhances the IOS. The first step calculates $\hat{\lambda}_{t,t+1} = x_{t,t+1} m_{t,t+1}$ for each period, where $x_{t,t+1}$ is the return to the hedge portfolio trading strategy and $m_{t,t+1}$ is the pricing kernel. Second, form the following h_T statistic:

$$h_T = T \left[\frac{1}{T} \sum_{k=0}^{T-1} \hat{\lambda}_{t+k,t+k+1} \right] W_T \left[\frac{1}{T} \sum_{k=0}^{T-1} \hat{\lambda}_{t+k,t+k+1} \right],$$

where W_T denotes the inverse of the variance of $\hat{\lambda}_{t,t+1}$. Under the null hypothesis that $E[\hat{\lambda}_{t,t+1}]$ is zero (i.e., that the strategy does not enhance the IOS), h_T is distributed asymptotically χ^2 with a

¹⁷ On the other hand, if the reference assets chosen in this paper do a poor job of spanning the IOS, then the documented results represent a lower bound on the ability of the pricing kernel to explain returns in my sample.

¹⁸ Specifically, I follow Ahn, Conrad, and Dittmar [2003] in sorting returns into 20 industry portfolios using the industry definitions of Moskowitz and Grinblatt [1999].

single degree of freedom. Later in the paper I use this test to examine if drift enhances the IOS available to investors.

Table 3 provides descriptive statistics for the pricing kernel. The mean is .995 with a standard deviation of .381. The mean of .995 implies that the monthly rate on the riskless asset was approximately .5%, or about 6.0% per year for the 1975 through 2002 period.¹⁹

In the following earnings-based and Mishkin [1983] analyses, I cumulate the monthly pricing kernel into a firm-quarter specific pricing kernel. The pricing kernel is firm-quarter-specific because firms have different return accumulation periods. The cumulation window for the firm-quarter-specific pricing kernel is the same window as for quarterly returns. That is, I cumulate the monthly observations on the pricing kernel starting with the month *after* the announcement month for quarter t earnings through the announcement month of quarter $t+1$ earnings. Panel A of Table 3 also presents descriptive statistics on the cumulative firm-quarter-specific pricing kernel. The mean is slightly above 1 with a standard deviation of 0.711.

The expected value for the pricing kernel should be less than one over any particular time period. The sample mean slightly greater than one indicates some measurement error, as expected with any empirical proxy. To assess the severity of the measurement error and to demonstrate the power of the pricing kernel as an explanatory variable for returns, I assess the ability of the cumulative pricing kernel to explain the quarterly returns for my sample. Panel B reports results from estimating the following firm-specific regression:²⁰

$$\left(CR_{t,t+1} - R_{t,t+1}^f\right) = a + d_1 m_{t,t+1} + d_2 MKT_{t,t+1} + d_3 SMB_{t,t+1} + d_4 HML_{t,t+1} + e_{t,t+1}, \quad (4)$$

¹⁹ The expected value of the pricing kernel is the inverse of the riskless rate:

$$1 = E\left[R_{t,t+1}^f m_{t,t+1}\right] = E\left[R_{t,t+1}^f\right]E\left[m_{t,t+1}\right] + \text{cov}\left(R_{t,t+1}^f, m_{t,t+1}\right) = R_{t,t+1}^f E\left[m_{t,t+1}\right]; \quad E\left[m_{t,t+1}\right] = \left(R_{t,t+1}^f\right)^{-1}.$$

²⁰ I suppress firm subscripts throughout the paper.

where *CR* denotes the cumulative return, *MKT* denotes the excess return on the market portfolio, *SMB* denotes the Fama-French size factor, and *HML* denotes the Fama-French book-to-market factor. Returns for all factors are cumulative over the month after announcement of earnings for quarter t through the month of announcement of earnings for quarter $t+1$.

The first specification regresses cumulative excess returns on the pricing kernel. The coefficient for the pricing kernel is negative and significant. Specifications (2), (3), (4) and (5) demonstrate the ability of the Fama-French factors to individually and collectively explain the returns for sample firms. Specifications (6), (7), (8), and (9) examine the incremental explanatory power of the pricing kernel. In particular, the market portfolio subsumes much of the explanatory ability of the pricing kernel, while the pricing kernel has incremental explanatory power relative to the size and book-to-market factors.²¹ However, expression (10) demonstrates that the pricing kernel remains a powerful explanatory variable for returns in the presence of the size and book-to-market factors. In theory, the pricing kernel should exactly price all assets in the economy (Cochrane [2001]). The results in Panel B highlight the substantial measurement error in estimating the pricing kernel.

The results in Panel B confirm that the pricing kernel I extract has significant explanatory power for returns and captures some of the same elements of risk as the market factor. The results also indicate that the market factor performs substantially better than the pricing kernel in explaining returns. As a practical matter, the market portfolio has had little success in explaining drift in prior research. Indeed, the hedge portfolio returns reported in later analyses have no significant association with the market portfolio but are significantly negatively associated with the pricing kernel. Moreover, the earnings-based results reported in Section VI are generally

²¹ However, the h -statistic of Chen and Knez [1996] reveals that neither the *MKT* nor *SMB* factors significantly enhance the IOS relative to the pricing kernel. However, the *HML* factor does enhance the IOS ($h=11.00$, $p < .001$).

stronger when using the pricing kernel to proxy for the theoretical construct of interest (i.e., investor IMRS) than when using the market portfolio (which, when replacing $m_{t,t+1}$, does enter the regressions with a significant positive interaction with SDE in most of the earnings specifications). Later analysis demonstrates that the pricing kernel conditioned on SDE loads in firm-specific and portfolio-level returns regressions and is robust to inclusion of the Fama-French factors. Finally, the implication of research advocating SDE-based portfolios as an additional factor is that common factor pricing models do not capture the underlying phenomenon that gives rise to drift, suggesting an alternative approach is preferable. Consequently, I adopt the pricing kernel as the primary measure of investor IMRS in the subsequent analysis.

V. EARNINGS-BASED TESTS

My first set of tests analyzes the variation in SDE autocorrelation. This analysis assesses the validity of prior work's assumption that autocorrelation has no systematic variation. I pursue this question in three ways. First, I examine whether autocorrelation varies with macroeconomic activity. Second, I assess whether the temporal variation in SDE autocorrelation is common across firms and for firms with extreme SDE. Third, I assess whether autocorrelation varies with a measure of investors' IMRS.

For each of these analyses, I estimate a SDE autoregression where I allow the autocorrelation for the first and fourth SDE lags to vary as a function of another variable that reflects economically-meaningful variation. To assess the link between the macroeconomy and autocorrelation, I allow autocorrelation to temporally vary with unexpected future growth in real GDP. An association between unexpected future GDP growth and autocorrelation suggests that

autocorrelation provides, or correlates with, information about economic conditions that likely matter to investors, and is therefore likely associated with investor consumption decisions. To assess whether autocorrelation reflects temporal variation that is common across firms, I allow SDE autocorrelation to vary with an ‘autocorrelation index’ in firm-specific regressions. I construct this autocorrelation index with the time-series of autocorrelation coefficients from quarterly cross-sectional regressions using an independent sample of firms. A systematic component to the temporal variation of SDE autocorrelation is a necessary condition for autocorrelation risk to contribute to post-earnings-announcement drift. An association between firms’ autocorrelation coefficients and aggregate variation in the autocorrelation index suggests a systematic element to the variation in SDE autocorrelation that cannot be diversified away. Finally, I assess whether the variation in SDE autocorrelation is consistent with autocorrelation risk as a contributing source of drift by allowing autocorrelation to vary with a measure of investors’ IMRS. Under the assumption that the pricing kernel is a valid measure of investors’ IMRS, negative covariance between autocorrelation and the pricing kernel is a sufficient condition for autocorrelation risk to contribute to post-earnings-announcement drift.

Autocorrelation and economic growth

To assess the relation between autocorrelation and economic growth, I estimate the following model:

$$SDE_{t+1} = a + (b_{10} + b_{11} * UGDPgr)SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41} * UGDPgr)SDE_{t-3} + b_{50}UGDPgr + e_{t+1} \quad (5)$$

where $UGDPgr$ denotes unexpected growth in GDP. I use seasonally-adjusted real GDP collected from the St. Louis Federal Reserve. I calculate growth in GDP ($GDPgr$) as current quarter GDP minus prior quarter GDP divided by prior quarter GDP. I use the following expectations model for one-period-ahead growth in GDP:

$$E(GDPgr_{t+1}) = .005 + .326 * GDPgr_t$$

based on parameter estimates from real GDP data from 1954 through 2004.²² I calculate unexpected GDP growth as realized GDP growth minus the applicable GDP growth expectation. I iterate the expectations model to develop expectations more than one period ahead.²³

Table 4 reports the results. Because the relation between firm earnings and the macroeconomy is not fully understood, I probe the link between SDE autocorrelation and unexpected GDP growth over a number of future periods. The interaction between $UGDPgr$ and SDE_t is generally positive across the subsequent eight quarters, while the interaction with SDE_{t-3} demonstrates several positive and negative associations over the same intervals. For the combined eight periods, I find that current SDE autocorrelation has a significant relation with $UGDPgr$. The association between $UGDPgr$ and autocorrelation for the fourth SDE lag is not statistically significant over this interval.

Table 4 documents that current autocorrelation correlates with unexpected future GDP growth. Consumption decisions depend, in part, on expectations of future economic conditions. News that future GDP growth will be higher than previously expected leads to a current increase (decrease) in consumption (marginal utility) holding all else equal. If higher than expected autocorrelation reveals or is correlated with information that suggests higher than expected GDP growth in future periods, then autocorrelation will positively (negatively) vary with consumption (marginal utility). Such negative co-variation between marginal utility and autocorrelation could lead investors to discount autocorrelation when impounding their expectations into price.

²² The parameter estimates are fairly stable over time. The (intercept, persistence) estimates for the 1954-1975 period are (.005,.362) while the estimates for the 1954-1990 period are (.005,.324). The results are not sensitive to the choice of estimation period. A check of the autocorrelation in the residuals did not reject the hypothesis that the residuals were white noise.

²³ For example, to estimate expected GDP growth two periods ahead, I use current GDP growth to estimate expected one-period-ahead GDP growth then enter the this growth estimate back into the model to estimate the two-period-ahead growth estimate

Systematic temporal variation in autocorrelation

I examine the systematic temporal variation in autocorrelation coefficients for three cuts of the sample: (1) firms with enough observations to estimate firm-specific SDE autoregressions, (2) firms in extreme deciles of SDE_t , and (3) firms in extreme deciles of SDE_{t-3} . For each of these three analyses (firm-specific, SDE_t and SDE_{t-3}), I follow a three-step procedure. First, I assign all observations to either an index subsample or a test subsample. For the firm-specific analysis, the test subsample includes all firms with a minimum of 40 observations.²⁴ For the SDE_t (SDE_{t-3}) analysis, the test subsample includes all observations in the highest and lowest deciles of SDE_t (SDE_{t-3}) each quarter. The index subsample for each analysis contains all observations not in the respective test subsample.

Second, I use each index subsample to construct a time-series of earnings autocorrelation coefficients by estimating the following equation in each quarterly cross-section:²⁵

$$SDE_{i,t+1} = a_{t+1} + b_{1,t+1}SDE_{i,t} + b_{2,t+1}SDE_{i,t-1} + b_{3,t+1}SDE_{i,t-2} + b_{4,t+1}SDE_{i,t-3} + e_{i,t+1}. \quad (6)$$

I use the time-series of the $b_{1,t+1}$ coefficients as an ‘autocorrelation index’ to examine whether the autocorrelation within each of the test subsamples possesses systematic temporal variation. Table 5, Panel A reports the results of estimating (6) for each of the three index subsamples.

Third, I estimate the following equation to assess the systematic temporal variation in autocorrelation coefficients for each of the test subsamples:²⁶

²⁴ The results are sensitive to the choice of 40 observations as the cutoff for the index and test subsamples. As the cutoff increases, so does the significance of the interaction between SDE and the index. This could reflect the greater precision in the firm-specific regression estimates as the number of observations used in those regressions increase. This would confirm the importance of using a sufficiently long time-series for estimating the firm-specific regressions.

²⁵ I use four lags in this model for consistency with other analyses. The results are unchanged when using an AR(1).

²⁶ I expect $b_{1,t+1}$ to vary as a function of fiscal quarter. In particular, the integral approach to quarterly earnings should lead $b_{1,t+1}$ to be systematically lower when it reflects the autocorrelation of fourth quarter earnings of one year for the first fiscal quarter of the next year (Rangan and Sloan [1998]). Thus, I measure $b_{1,t+1}$ as deviation from the mean, where the mean is the average autocorrelation for that fiscal quarter over the 28 years in my sample. I also estimated a modified form of (7) that includes interactions between SDE and an indicator that takes the value of 1 if

$$SDE_{t+1} = a + (b_{10} + b_{11}I_{t+1})SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41}I_{t+1})SDE_{t-3} + b_{50}I_{t+1} + b_{60}\hat{a}_{t+1} + e_{t+1} \quad (7)$$

where I_{t+1} and \hat{a}_{t+1} denote the autocorrelation index (i.e., the fiscal-quarter-mean-adjusted $b_{1,t+1}$) and intercept, respectively, estimated from (6) using the applicable test subsample (firm-specific, SDE_t , or SDE_{t-3}). Because the index regressions allow the intercepts to vary over time, I include the intercepts from these regressions as a separate control variable. The b_{11} and b_{41} coefficients indicate the extent to which autocorrelation coefficients for the first and four lags vary with the index. A significant positive (negative) relation between the index and autocorrelation for the first (fourth) lag of SDE suggests that autocorrelation contains a systematic temporal element consistent with post-earnings-announcement drift.

Table 5, Panel B reports the average of the firm-specific regression coefficients without the index in column (1) and with the index in column (2). Autocorrelation for the first (fourth) SDE lag significantly positively (negatively) co-varies with the index. These results indicate that SDE autocorrelation reflects systematic variation. This systematic temporal variation is consistent with the contribution of autocorrelation risk to post-earnings-announcement drift. Importantly, the covariation with the index reverses sign for the last SDE lag. This suggests that the troubling reversal of sign in the relation between current SDE and future abnormal returns four quarters ahead documented by Bernard and Thomas [1990] could be consistent with a risk-based explanation.

I perform similar analysis to assess whether these inferences extend to the autocorrelation of firms in the extreme deciles of the SDE distribution. I report the results of estimating (7) for the highest and lowest deciles of the SDE_t distribution in columns (3) and (4) of Table 5, Panel

the first lag is for the fourth fiscal quarter. The results were qualitatively the same as those reported in Table 4. These results demonstrate that the inferences are not driven by the lower autocorrelation of fourth fiscal quarter earnings for earnings of the first fiscal quarter of the next year (Rangan and Sloan [1998]).

B.²⁷ The $I_{t+1} * SDE_t$ interaction is of interest here. The results indicate that autocorrelation coefficients for firms in both extremes of the SDE_t distribution positively covary with the index. This suggests that the autocorrelation for firms in extreme SDE deciles possesses common temporal variation.

I report the results for the lowest and highest deciles of the SDE_{t-3} distribution in columns (5) and (6), respectively. The coefficient of the $I_{t+1} * SDE_{t-3}$ interaction is of interest here. The results indicate that the autocorrelation for firms in the lowest decile, but not the highest decile, of the SDE_{t-3} distribution *negatively* covaries with the index. These results for the lowest decile provide additional evidence that the negative relation between SDE and abnormal returns four-quarters-ahead could relate to risk.

The association between autocorrelation and the pricing kernel

To examine the relation between autocorrelation and the pricing kernel, I estimate the following regression:

$$SDE_{t+1} = a + (b_{10} + b_{11}m_{t,t+1})SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41}m_{t,t+1})SDE_{t-3} + b_{50}m_{t,t+1} + e_{t+1} \quad (8)$$

where all variables have been previously defined. Table 6 reports the results from firm-specific regressions, pooled sample regressions, and regressions for observations in extreme deciles of SDE_t and SDE_{t-3} .²⁸ The firm-specific regressions allow for a comparison of the pricing kernel evidence with the autocorrelation index evidence of Table 5. The significant negative relation between autocorrelation and the pricing kernel for the first lag supports the autocorrelation risk model's prediction. In addition, the negative coefficient here is consistent with the positive

²⁷ For the SDE_t and SDE_{t-3} subsample analysis, I first remove any observation with an absolute value of studentized residual greater than 2.

²⁸ To verify that the results are not sensitive to the lower autocorrelation of the fourth fiscal quarter SDE, I estimated the full sample results excluding those observations. Inferences are unchanged.

coefficient from the firm-specific results in Table 5 as well as the positive coefficient from the economic growth results in Table 4. The results for the fourth lag are not significant.

The results for the full (pooled) sample reveal a significant negative estimate of b_{11} . On the other hand, b_{41} is not significant. The replication results in Table 2 imply that the relation between autocorrelation and the pricing kernel should be considerably stronger for the first lag than for the fourth lag. In light of this, I view the firm-specific and full sample results as generally supportive of the autocorrelation risk model, at least for the first lag.

I also estimate (8) for observations in extreme deciles of SDE_t and SDE_{t-3} . This subsample evidence is important because it demonstrates whether the implications of the autocorrelation risk model hold in the extreme deciles that have served as the focus of much of the prior drift literature. The results consistently indicate a negative association between the pricing kernel and autocorrelation for the first lag of SDE. This is consistent with risk contributing to post-earnings-announcement drift for the first lag of SDE. The evidence for the fourth lag of SDE is inconsistent. Overall, I interpret the results in Table 6 as supportive of the autocorrelation risk model's predictions for the relation between autocorrelation and the pricing kernel for the first lag of SDE. Given the failure to find consistent results for the fourth lag of SDE, the returns-based analysis discussed next focuses on autocorrelation risk in the first SDE lag only.

VI. RETURNS-BASED TESTS

The earnings-based results reported in the previous section document patterns of variation in SDE autocorrelation consistent with autocorrelation risk as a contributing source of post-earnings-announcement drift. These results stand in contrast to the assumption maintained

in prior work that autocorrelation possesses no systematic variation. In this section, I examine the consequences of autocorrelation risk for post-earnings-announcement drift returns. First, I assess whether the covariance between returns and the pricing kernel depend on current SDE, as predicted by the autocorrelation risk model. Second, I analyze the returns for extreme SDE deciles to assess the ability of size-decile benchmark returns to control for autocorrelation risk. Third, I examine hedge portfolio returns to identify the economic significance of autocorrelation risk for post-earnings-announcement drift returns. Finally, I examine the effect of controlling for autocorrelation risk on the bias in the autocorrelation coefficients impounded in price. I generally use monthly intervals for returns, the pricing kernel, and the Fama-French factors. The exception is the Mishkin analysis, in which I use a quarterly interval.

Analysis of risk in returns

I examine the prediction that risk in returns depends on recent SDE by estimating the following model on a firm-specific basis for firms with at least 60 months of returns:

$$\begin{aligned}
 ExRet_{t,t+1} = & \delta_0 + \delta_1 SDE_t + \delta_2 m_{t,t+1} + \delta_3 SDE_t * m_{t,t+1} + \delta_4 MKT_{t,t+1} \\
 & + \delta_5 SMB_{t,t+1} + \delta_6 HML_{t,t+1} + \varepsilon_{t,t+1}
 \end{aligned} \tag{9}$$

where $ExRet_{t,t+1}$ denotes the firm's excess return (raw return minus the return on the one-month T-Bill) for the month ending at $t+1$ and SDE_t is computed using the firm's most recently announced earnings as of the end of month t . The autocorrelation risk model predicts that $SDE_t * m_{t,t+1}$ will be significantly negatively associated with excess returns. The results, reported in Table 7, Panel A, are consistent with the predictions of the autocorrelation risk model. The results suggest the covariance between excess returns and the pricing kernel is conditional on current SDE_t . Moreover, this result is robust to the inclusion of the Fama-French factors.

I extend the analysis to examine excess returns for decile portfolios formed on SDE_t . First, I sort each monthly return in my sample into decile portfolios based on the most recent SDE_t decile rank for that firm. Each month, I average excess returns within deciles to form a time-series of monthly observations for each SDE_t decile. To examine whether these decile portfolio excess returns reflect risk that depends on SDE, I estimate the following regression:

$$\begin{aligned}
DecExRet_{t,t+1} = & \delta_0 + \delta_1 RSDE_t + \delta_2 m_{t,t+1} + \delta_3 RSDE_t * m_{t,t+1} \\
& + \delta_4 MKT_{t,t+1} + \delta_5 SMB_{t,t+1} + \delta_6 HML_{t,t+1} + \varepsilon_{t,t+1}
\end{aligned} \tag{10}$$

where $DecExRet_{t,t+1}$ denotes the decile excess return for the month ending at $t+1$ and $RSDE_t$ denotes the portfolio's SDE_t decile rank, scaled to the interval (0,1). The coefficient on $RSDE_t$ has the interpretation as the average difference in returns between the highest and lowest deciles of SDE_t . I expect $RSDE_t$ to load with a positive coefficient and the pricing kernel to load with a negative coefficient. The autocorrelation risk model predicts that risk reflected in returns is conditional on SDE_t . Thus, I predict that the interaction term will load with a significant negative coefficient.

Table 7, Panel B reports the results. $RSDE_t$ loads with a significant positive coefficient of 0.014. This suggests that the average difference in monthly returns between the highest and lowest SDE_t firms is about 1.4%. This corresponds to a 4.2% quarterly return, which is close to the quarterly return of 4.7% documented in specification 2 of Table 2, Panel A. The interaction term loads with a significant negative coefficient. The interaction term remains negative and its significance level increases in the presence of the Fama-French risk factors. Thus, the results support the prediction of the autocorrelation risk model.

The results in Table 7 provide an opportunity to assess the economic significance of the conditional risk adjustment implied by the autocorrelation risk model. The descriptive statistics for the pricing kernel in panel A of Table 2 report a standard deviation of 0.381. Using the results

in Panel B, Table 7, a one standard deviation increase in the pricing kernel corresponds to a decline in the difference in returns across extreme decile portfolios of roughly 0.007 (.381 x .018) – about a 50% drop. This suggests that a portfolio strategy based on SDE delivers unexpectedly low returns when consumption is unexpectedly scarce (when the pricing kernel is unexpectedly high).

Risk differences in extreme SDE portfolios

Consistent with the results from the last section, I expect that the coefficient on the pricing kernel will be significantly lower for the high SDE_t decile relative to the low SDE_t decile in a regression of excess decile-month returns. This will indicate that the firms in the highest SDE decile are riskier than the firms in the lowest SDE decile. In addition, I expect that the coefficient on the pricing kernel will be significantly negative for the high SDE_t decile but significantly *positive* for the low SDE_t decile in a regression of size-adjusted returns. This is because size-adjusted returns likely control for the other elements of risk identified in expression (1) but not for autocorrelation risk, which is scaled by the portfolio formation variable. This analysis is important because it assesses the adequacy of size-based controls for risk when studying post-earnings-announcement drift returns.

I estimate the following two expressions for the high and low SDE_t decile portfolios:

$$DecExRet_{t,t+1} = \alpha_{t+1} + \beta_{t+1}m_{t,t+1} + \varepsilon_{t,t+1} \quad (11)$$

$$SADecRet_{t,t+1} = \alpha_{t+1} + \beta_{t+1}m_{t,t+1} + \varepsilon_{t,t+1} \quad (12)$$

where $DecExRet_{t,t+1}$ is the decile excess return for month $t+1$ using firm's excess returns (raw returns minus the return on the 1 month T-Bill) and $SADecRet_{t,t+1}$ is the decile portfolio return for month $t+1$ using firms' size-adjusted returns. In (11), the coefficient on the pricing kernel captures the effects of all three components of expected returns in (1). Accordingly, I expect a

negative coefficient for both extreme deciles, but I expect the high SDE_t decile to be significantly less than the low SDE_t decile. In (12), I use size-decile returns to control for $cov(m_{t,t+1}, v_{t,t+1})$ and $cov(m_{t,t+1}, e_{t+1})$ from expression (1). After controlling for size-decile returns, the model in (1) predicts that expected returns will vary with SDE. In addition, (1) suggests that *expected returns* should be positive for high SDE firms but negative for low SDE firms. Thus, I expect the *pricing kernel* to load with a significant negative (positive) coefficient for the highest (lowest) SDE_t decile in expression (12).

Table 8 reports the results. As predicted, the coefficient for the high SDE_t decile is significantly more negative than the average coefficient for the low SDE_t decile in specification (1) ($t = -1.69$, $p < 0.05$, in a one-tailed test, not tabulated). This indicates that the risk in the high SDE_t decile exceeds the risk in the low SDE_t decile. To assess the adequacy of size-adjusted returns, I examine the relation between size-adjusted returns and the pricing kernel. As predicted, I find that the loading on the pricing kernel for the lowest SDE_t decile is significantly positive, while the loading on the pricing kernel for the highest SDE_t decile is significantly negative. This provides corroborating evidence that risk is correlated with SDE_t and not completely captured by size-decile portfolio returns. This evidence is consistent with the autocorrelation risk model developed in this paper.²⁹

Analysis of hedge portfolio returns

Analysis of hedge portfolio returns provides corroborating evidence that the risk in returns is correlated with SDE and that SDE hedge portfolio returns negatively covary with the

²⁹ However, these results are also consistent with other risk-based explanations that might make this same prediction. One such explanation appears in Sadka and Sadka [2003]. They find that extreme portfolios sorted on seasonally-differenced earnings are associated with differences in liquidity, and they suggest that these liquidity differences contribute to drift. However, they do not address how liquidity relates to evidence of seemingly biased expectations in price, which is arguably the most compelling evidence associated with the anomaly. In addition, it is not clear that the pricing kernel used here would reflect the effects of ‘liquidity risk.’

pricing kernel. In addition, this analysis provides an opportunity to formally test whether drift significantly expands the IOS and to assess the contribution of autocorrelation risk to the expected returns in SDE hedge portfolios. I analyze hedge portfolio returns by estimating the following model:

$$HedgeRet_{t,t+1} = \delta_0 + \delta_1 m_{t,t+1} + \delta_2 MKT_{t,t+1} + \delta_3 SMB_{t,t+1} + \delta_4 HML_{t,t+1} + \varepsilon_{t,t+1} \quad (13)$$

where *HedgeRet* is the return to the highest SDE decile portfolio minus the return to the lowest SDE decile portfolio.

I report the results in Table 9. First, note that the average monthly return to the hedge portfolio is 1.4%, consistent with prior results. The market portfolio captures none of this variation. On the other hand, the pricing kernel suggests that at least a portion of this return is attributable to risk. In particular, these results suggest that almost 20% of the average return to the hedge portfolio is compensation for risk (coefficient x variance / average returns = .018 x .145 / .014). Not surprisingly given these results, the null hypothesis that the drift strategy does not enhance the IOS is rejected ($h_T = 29.25$, $p < 0.001$, not tabulated).

The intercept increases once the Fama-French factors are included, suggesting the risk-adjusted returns are even *higher* than the raw returns suggest. However, including the pricing kernel once again suggests that some of the hedge portfolio returns reflect risk. In fact, these results suggest that over 23% of the average returns to SDE hedge portfolio reflects risk (coefficient x variance / average returns = .024 x .145 / .015).

Mishkin analysis

The earnings-based analysis provides supporting evidence for the autocorrelation risk model. In addition, results in Tables 7, 8, and 9 suggest that the appropriate risk adjustment depends on SDE_t as predicted by the autocorrelation risk model. Collectively, this evidence

suggests that autocorrelation risk plays a role in post-earnings-announcement drift. To examine the impact of autocorrelation risk on the implied autocorrelation from stock prices, I estimate the following system of equations using nonlinear least squares:

$$\begin{aligned}
SDE_{t+1} &= a + b_{10}SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + b_{40}SDE_{t-3} + e_{t+1} \\
CR_{t,t+1} &= \phi_0 + \phi_1[SDE_{t+1} - (a + b'_{10}SDE_t + b'_{20}SDE_{t-1} + b'_{30}SDE_{t-2} + b'_{40}SDE_{t-3})] \\
&\quad + (\phi_{20} + \phi_{21}SDE_t)m_{t,t+1} + \varepsilon_{t,t+1}
\end{aligned} \tag{14}$$

The earnings regression represents an objective expectations model against which the expectations impounded in price can be compared. As an expectations model, it is not appropriate to include variables that are not known at the time expectations in prices are formed (i.e., the beginning of the return cumulation window) (Mishkin [1984, 13]). Consequently, I omit the pricing kernel and the interaction between the pricing kernel and SDE_t from the objective expectations model. This omission has little effect relative to the coefficients reported in prior tables because I recast the pricing kernel as deviations from the mean. I control for expected returns in assessing the expectations impounded in price. This is particularly important here because expected returns should vary with a variable used to develop expectations. To control for expected returns I include the pricing kernel and the interaction between the pricing kernel and SDE_t in the returns equation. If autocorrelation risk contributes to drift, I expect the implied autocorrelation of SDE_t from stock prices to be closer to the actual autocorrelation from the earnings regression when controlling for the interaction between autocorrelation and the pricing kernel.

Table 10 reports the results. The first specification reproduces the results from Table 2 for ease of comparison. The second specification includes the pricing kernel as a control in the returns regression. I expect these results to be very similar to those in Table 2. This is because the autocorrelation risk model predicts that the risk is conditional on the sign and magnitude of

SDE_t , and the first specification does not incorporate this conditioning. As expected, the results for the first specification are nearly identical to the results in Table 2. Specification (3) conditions the risk control on SDE_t . Given the results in prior tables, I predict that this specification will at least partially control for the effect of autocorrelation risk on the implied autocorrelation coefficient on SDE_t . As with specification (2), however, the evidence of seemingly biased expectations in stock prices changes very little. Overall, the evidence from the Mishkin [1983] analysis provides little support for the autocorrelation risk model.

The ability to discriminate the market's expectation of autocorrelation from the related risk adjustment depends on the ability to measure the covariance between autocorrelation and the pricing kernel. The results from Table 6 suggest that the model in (14) may not perform very well in this regard. For example, the coefficient on the interaction term between the pricing kernel and seasonally-differenced earnings for the pooled sample in Table 6 is -0.033. Autocorrelation declines by 0.033 for each unit change in the pricing kernel. The standard deviation of the pricing kernel in this regression is 0.711 (from Table 3). Thus, a one standard deviation increase in the pricing kernel corresponds to a -.023 (-0.033 x .711) change in autocorrelation. The covariance between pricing kernel and autocorrelation for the first lag must be approximately -0.199 (.230 - .429, from Panel A) to completely explain the evidence of seemingly biased expectations in price. While not directly comparable, this covariance is almost nine times the change in autocorrelation for a one standard deviation change in the pricing kernel. Consequently, I suspect the difference stems in part from variable measurement or model specification problems. Nevertheless, the preponderance of the evidence reported in this paper supports the autocorrelation risk model, suggesting that autocorrelation risk contributes to but does not fully explain post-earnings-announcement drift.

VI. CONCLUSION

This paper examines the role of autocorrelation risk in post-earnings-announcement drift. Autocorrelation risk refers to the co-variation between earnings autocorrelation and investor intertemporal marginal rate of substitution, or pricing kernel. Rational investors should impound earnings information into price as if they adjust autocorrelation coefficients to certainty equivalents to reflect autocorrelation risk, if it exists. Use of certainty-equivalent-adjusted autocorrelation coefficients could produce or contribute to post-earnings-announcement drift and the appearance of biased expectations impounded in price. Instead of reflecting a naïve understanding of the process that generates earnings, such biased autocorrelation coefficients would rationally reflect the risk inherent in seasonally-differenced earnings autocorrelation.

In this paper, I analytically demonstrate that biased autocorrelation coefficients impounded into stock prices do not necessarily rule out risk-based explanations. The model I develop demonstrates that the implied autocorrelation from stock prices will deviate from the objective autocorrelation estimated from earnings data if autocorrelation co-varies with the pricing kernel. The model also indicates that the appropriate risk adjustment depends on the most recent seasonally-differenced earnings.

In tests of the model's implications, I find that earnings autocorrelation positively co-varies with unexpected future business conditions that likely matter to investors. Second, I test for and find a systematic temporal component in the earnings autocorrelation across firms, a necessary condition for the market to price autocorrelation risk. Third, I test for and find negative co-variation between earnings autocorrelation and the pricing kernel, a sufficient condition for the market to price autocorrelation risk. Fourth, I find that the risk reflected in returns depends on

current seasonally-differenced earnings as predicted by the autocorrelation risk model. This relation is economically significant; a one-standard-deviation increase in the pricing kernel corresponds to a 50% reduction in the returns to hedge portfolios formed on extreme seasonally-differenced earnings. Finally, I examine the extent to which autocorrelation risk contributes to seemingly-biased autocorrelation coefficients impounded in price but the results do not support the autocorrelation risk model's implications. I believe that model specification problems contribute to this result. Nevertheless, the preponderance of evidence supports the autocorrelation risk model's predictions and suggests that autocorrelation risk contributes to post-earnings-announcement drift.

APPENDIX A. A NUMERICAL EXAMPLE OF AUTOCORRELATION RISK

The value (v) to a risk-averse investor of any payoff in a contingent claims market is given by summing across future contingent events the product of (1) the probability, p , that the event will occur, (2) the intertemporal marginal rate of substitution (also called pricing kernel), denoted m , which reflects the value of additional consumption in that event, and (3) the event-contingent payoff, in this case SDE :

$$v^0 = \sum_{s=1}^S p_s^1 m_s^1 SDE_s^1$$

where $s \in S$ denotes the event (or state) and the superscript denotes the time index. Assume that next period SDE is the product of current SDE and event-contingent autocorrelation, φ . Then, the value of the payoff is given by:

$$v^0 = \sum_{s=1}^S p_s^1 m_s^1 (\varphi_s^1 SDE^0)$$

The expected value of SDE^1 , using probabilities only and ignoring differences in the value of additional consumption across states, is given by:

$$E^0(SDE^1) = \sum_{s=1}^S p_s^1 (\varphi_s^1 SDE^0)$$

The adjustment for risk is then the difference between the expected value of SDE^1 using probabilities only and the value attached to SDE^1 by the investor:

$$\text{Risk adjustment} = E^0(SDE^1) - v^0$$

To illustrate how event-contingent autocorrelation can contribute to the appearance that the market undervalues the implications of current positive SDE and overvalues the implications of current negative SDE , consider the following table that summarizes the probabilities, pricing kernel, and event-contingent autocorrelation across good and bad states:

Good States	p	.5
	m	.2
	φ	.6
Bad States	p	.5
	m	1.8
	φ	.2

The determination of good versus bad states is made on the basis of consumption. The pricing kernel is the ratio of marginal utility of consumption in period 1 to marginal utility in period 0. Low (high) m in a particular state implies relatively low (high) marginal utility in that state,

which implies high (low) consumption in that state. Thus, good states have relatively low m and bad states have relatively high m . Note that the autocorrelation coefficient is relatively high in good states and relatively low in bad states. Thus, the autocorrelation coefficient positively varies with consumption and *negatively* varies with the pricing kernel.

Next, consider two cases – the first where current SDE is 1 and the second where current SDE is -1:

	SDE^0 is	
	1	-1
$E^0(SDE^1)$.4	-.4
v^0	.24	-.24
Risk adjustment	.16	-.16

The table demonstrates that negative co-variation between the pricing kernel and the autocorrelation coefficients can produce the appearance that investors undervalue the implications of current positive SDE and overvalue the implications of current negative SDE . Current SDE of 1 (-1) implies .4 (-.4) SDE next period *on average*. However, the investor **rationaly** acts as if the current SDE of 1 (-1) implies .24 (-.24) SDE next period *on average* (from the expression for v_0 : $.5 \times .6 \times .2 + .5 \times .2 \times 1.8 = .24 \times 1$ (-1) = .24 (-.24)) The difference occurs because the investor considers risk and weighs the states differently in forming expectations relative to the expected value using the physical probabilities only.

To provide additional insight, consider again the risk adjustment:

$$\begin{aligned}
E^0(SDE^1) - v^0 &= \sum_s p_s^1 \varphi_s^1 SDE^0 - \sum_s p_s^1 \varphi_s^1 m_s^1 SDE^0 \\
&= \left[\sum_s p_s^1 \varphi_s^1 - \sum_s p_s^1 \varphi_s^1 m_s^1 \right] SDE^0 \\
&= \left[E(\varphi_s^1) - E(\varphi_s^1 m_s^1) \right] SDE^0 \\
&= \left[E(\varphi_s^1) - E(\varphi_s^1) E(m_s^1) - cov(\varphi_s^1, m_s^1) \right] SDE^0 \\
&= \left[-cov(\varphi_s^1, m_s^1) \right] SDE^0
\end{aligned}$$

The last equality holds because the expected value of the pricing kernel is 1 in this example. Thus, the risk adjustment is the product of autocorrelation risk, $cov(\varphi_s^1, m_s^1)$, and current SDE . Current SDE scales autocorrelation risk such that changing the sign and magnitude of current SDE changes the sign and magnitude of the risk adjustment associated with autocorrelation risk.

APPENDIX B. ADDITIONAL DISCUSSION OF THE AUTOCORRELATION RISK MODEL

First, I assume no arbitrage, which holds that investors cannot create portfolios with strictly positive expected returns but that will certainly never cost anything (i.e., no initial investment and no chance of loss in the future). No Arbitrage represents the minimum characterization of investor preferences to ensure that an equilibrium exists in capital markets (Harrison and Kreps [1979], Rubinstein [1976], Cochrane [2001], Christensen and Feltham [2003]). In equilibrium, an investor's optimal consumption and investment decision with respect to a particular asset satisfies the following first order condition:

$$p_t u'(c_t) = \beta E[x_{t+1} u'(c_{t+1})], \quad (\text{B1})$$

where p_t denotes the price of the asset at time t , $u'(c_t)$ denotes marginal utility for consumption at time t , β denotes the investor's subjective discount factor (time preference for consumption ignoring risk), x_{t+1} denotes the asset's payoff at time $t+1$. This expression states that, in equilibrium, the marginal utility cost of foregoing consumption and investing a little more in the asset today must equal the (time-discounted) expected marginal utility gain from the asset's payoff next period. Rearranging (B1) expresses price in terms of payoffs and the investor's intertemporal marginal rate of substitution:

$$p_t = E[x_{t+1} m_{t,t+1}], \quad (\text{B2})$$

where $m_{t,t+1} = \frac{\beta u'(c_{t+1})}{u'(c_t)}$ denotes the investor's intertemporal marginal rate of substitution, also called the pricing kernel. No arbitrage ensures that a (positive) pricing kernel exists that prices all assets in the economy (see Cochrane [2001] for a proof).

Normalizing expression (B2) by p_t and rearranging yields the following expression for expected returns:

$$E(R_{t,t+1}) = R_{t,t+1}^f [1 - \text{cov}(R_{t,t+1}, m_{t,t+1})], \quad (\text{B3})$$

where $R_{t,t+1} = x_{t+1} / p_t$ denotes gross return for the period ending at $t+1$, and $R_{t,t+1}^f$ denotes the gross return on the riskless asset for the period ending at $t+1$.³⁰ The covariance term reflects the risk of the asset. Note that an expected return in excess of the riskless rate is consistent with a *negative covariance* between returns and the pricing kernel.³¹

³⁰ The expected value of the pricing kernel is the inverse of the riskless rate:

$$1 = E[R_{t,t+1}^f m_{t,t+1}] = E[R_{t,t+1}^f] E[m_{t,t+1}] + \text{cov}(R_{t,t+1}^f, m_{t,t+1}) = R_{t,t+1}^f E[m_{t,t+1}]; \quad E[m_{t,t+1}] = (R_{t,t+1}^f)^{-1}.$$

³¹ Negative covariance with the pricing kernel implies negative covariance with future marginal utility, which implies positive covariance with future consumption. Thus, the negative covariance between a payoff and the pricing kernel suggests that the asset's payoff is greater than expected when consumption is unexpectedly high – when other assets also have high payoffs.

Second, I assume realized returns vary with expected returns and unexpected earnings (UE):

$$R_{t,t+1} = E(R_{t,t+1}) + \phi_1 UE_{t+1} + \nu_{t,t+1}, \quad (\text{B4})$$

where ϕ_1 denotes the earnings response coefficient (scaled by price) and $\nu_{t,t+1}$ reflects the impact of unanticipated other information (assumed orthogonal to unexpected earnings).

Third, I specify an earnings-generating process. Initially, I focus on an AR(1) process for seasonally-differenced earnings. However, the model is easily extended to include additional lags, and I will extend the model to an AR(4) process later. I assume that the following model, adapted from Foster [1977], well approximates the process that generates earnings:³²

$$SDE_{t+1} = b_{t+1} SDE_t + e_{t+1}, \quad (\text{B5})$$

where SDE_t denotes seasonally-differenced earnings (current quarter earnings less earnings from the corresponding quarter in the previous year) for the period ending at time t , and $b_{t+1} \sim N(E(b), \sigma_b^2)$. The subscript on b_{t+1} denotes that the implications of SDE_t for SDE_{t+1} are not known with certainty at the time SDE_t is revealed. Given expression (B5), the following equation expresses unexpected earnings:

$$UE_{t+1} = SDE_{t+1} - E(SDE_{t+1}) = [b_{t+1} - E(b)] SDE_t + e_{t+1}. \quad (\text{B6})$$

To develop an explicit characterization of expected returns, I substitute expressions (B4) and (B6) into (B3) and rearrange:

$$E(R_{t,t+1}) = R_{t,t+1}^f \left[1 - \phi_1 \text{cov}(m_{t,t+1}, b_{t+1}) SDE_t - \phi_1 \text{cov}(m_{t,t+1}, e_{t+1}) - \text{cov}(m_{t,t+1}, \nu_{t,t+1}) \right]. \quad (\text{B7})$$

The covariance terms on the right-hand side represent the risk inherent in returns implied by the autocorrelation risk model. Note that all random variables have a corresponding covariance term with the pricing kernel. Any non-zero covariance would represent an element of the risk adjustment.

I next depict realized returns by substituting expected returns from (B7) and expression (B6) into (B4):

$$R_{t,t+1} = R_{t,t+1}^f + \phi_1 \left(SDE_{t+1} - [E(b) + R_{t,t+1}^f \text{cov}(m_{t,t+1}, b_{t+1})] SDE_t \right) + \Phi_{t,t+1}, \quad (\text{B8})$$

where $\Phi_{t,t+1} = \nu_{t,t+1} - R_{t,t+1}^f \text{cov}(m_{t,t+1}, \nu_{t,t+1}) - R_{t,t+1}^f \phi_1 \text{cov}(m_{t,t+1}, e_{t+1})$. The model in (B8) resembles the non-linear least squares model used by Collins and Hribar [2001] and Kimbrough [2001].

³² Bernard and Thomas [1990] make a similar simplifying assumption.

Extending the earnings model to incorporate additional SDE lags yields the following model of returns:

$$R_{t,t+1} = R_{t,t+1}^f + \phi_1 (SDE_{t+1} - b'_{0,t+1} SDE_t - b'_{1,t+1} SDE_{t-1} - b'_{2,t+1} SDE_{t-2} - b'_{3,t+1} SDE_{t-3}) + \Phi_{t,t+1} \quad (\text{B9})$$

where:

$$b'_{0,t+1} = E(b_{0,t+1}) + R_{t,t+1}^f \text{cov}(b_{0,t+1}, m_{t,t+1})$$

$$b'_{1,t+1} = E(b_{1,t+1}) + R_{t,t+1}^f \text{cov}(b_{1,t+1}, m_{t,t+1})$$

$$b'_{2,t+1} = E(b_{2,t+1}) + R_{t,t+1}^f \text{cov}(b_{2,t+1}, m_{t,t+1})$$

$$b'_{3,t+1} = E(b_{3,t+1}) + R_{t,t+1}^f \text{cov}(b_{3,t+1}, m_{t,t+1})$$

Using the implied autocorrelation coefficients from returns regression and the actual autocorrelation coefficients from the earnings regression estimated from Panel B of Table 1 (and assuming an average quarterly riskless rate of approximately 1.5%) provides an indication of the sign and magnitude that these covariances must take for autocorrelation risk to fully explain drift in my sample:

$$b'_{0,t+1} = E(b_{0,t+1}) + R_{t,t+1}^f \text{cov}(b_{0,t+1}, m_{t,t+1})$$

$$0.230 = 0.429 + (1.015) (-0.196)$$

$$b'_{1,t+1} = E(b_{1,t+1}) + R_{t,t+1}^f \text{cov}(b_{1,t+1}, m_{t,t+1})$$

$$0.114 = 0.129 + (1.015) (-0.015)$$

$$b'_{2,t+1} = E(b_{2,t+1}) + R_{t,t+1}^f \text{cov}(b_{2,t+1}, m_{t,t+1})$$

$$0.088 = 0.074 + (1.015) (0.014)$$

$$b'_{3,t+1} = E(b_{3,t+1}) + R_{t,t+1}^f \text{cov}(b_{3,t+1}, m_{t,t+1})$$

$$-0.072 = -0.118 + (1.015) (0.045)$$

This suggests that the covariance is largest in magnitude for the first and fourth parameters, and that these covariances should take opposite signs.

APPENDIX C. ADDITIONAL DISCUSSION OF THE PRICING KERNEL

I employ a simple pricing kernel extracted from market data as in Hansen and Jagannathan [1991]. To illustrate this approach, consider the general pricing equation derived from expression (B2) for a given vector of payoffs \mathbf{x} at time $t+1$ and prices \mathbf{p} at time t :

$$\mathbf{p} = E_t[\mathbf{x}m_{t+1}]. \quad (\text{C1})$$

Asset pricing theory holds that the pricing kernel, m , exactly prices all assets in the economy. Suppose a unique payoff, that is a linear combination of payoffs in the \mathbf{x} vector, prices all the assets with prices \mathbf{p} and payoffs \mathbf{x} exactly. Such a payoff would take the form $x^* = \mathbf{c}'\mathbf{x}$ where \mathbf{c} describes the positions that the portfolio takes in the assets. Then,

$$\begin{aligned} \mathbf{p} &= E_t[\mathbf{x}x^*] \\ \mathbf{p} &= E_t[\mathbf{x}\mathbf{x}'\mathbf{c}] \\ E_t[\mathbf{x}\mathbf{x}']^{-1}\mathbf{p} &= \mathbf{c} \end{aligned}$$

and, $m_{t,t+1} = x^* = \mathbf{p}'E_t[\mathbf{x}\mathbf{x}']^{-1}\mathbf{x}$, (C2)

Hansen and Jagannathan [1991] note that expression (C2) relies only on the first moments of prices and the second moments of returns. Thus, researchers can extract the pricing kernel from observed market data.

Expression (C2) implicitly assumes the law of one price and free portfolio formation. The law of one price basically states that two assets that have identical payoffs (across all possible contingent events) must have identical prices. The law of one price represents a weak characterization of investor preferences (Cochrane [2001]) – investors will not leave violations of the law of one price on the table. Free portfolio formation is a simplifying assumption that no restrictions, such as short-sale constraints, prevent taking the positions in \mathbf{c} .

The assets with prices \mathbf{p} and payoffs \mathbf{x} are called reference assets. The degree to which x^* approximates the true pricing kernel³³ depends on the degree to which the reference assets span the investment opportunity set (IOS) available to investors. If the basis assets do a reasonable job in spanning the IOS, x^* should approximate the true pricing kernel reasonably well. If the basis assets do not span the IOS, then the ability of x^* to approximate the true pricing kernel diminishes.

I follow Ahn Conrad, and Dittmar [2003] (who follow Moskowitz and Grinblatt [1999]) in selecting 20 industry-sorted portfolios as the basis assets. I scale these portfolios to have prices equal to 1 and payoffs equal to the gross realized portfolio returns. Ahn, Conrad, and Dittmar [2003] point out that the industry-sorted portfolios minimize cross-group correlation. By minimizing cross-group correlation, each industry portfolio adds to the IOS over and above what other portfolios add.

³³ More carefully, x^* approximates the projection of the true pricing kernel onto the payoff space defined by the reference assets. See Cochrane (2001), Chapter 4.

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Table 1. Descriptive Statistics

<i>Variable</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>First Quartile</i>	<i>Median</i>	<i>Third Quartile</i>
Quarterly earnings (\$MM)	54.641	260.001	0.919	6.151	29.617
Seasonal change in earnings (\$MM)	4.030	77.380	-1.000	0.442	3.701
<i>SDE</i> (scaled by historical std. dev.)	0.440	1.681	-0.535	0.319	1.327
<i>CR</i>	0.039	0.273	-0.089	0.021	0.138
<i>MVE</i> (\$MM)	1863.320	9797.430	53.457	217.548	934.504

Notes to Table 1. The sample includes 117,614 firm-quarter observations from 1975:3 to 2002:12.

Variable Definitions:

Quarterly Earnings = Operating income after depreciation.

Seasonal change in earnings = Current quarter earnings – earnings for the same quarter in the prior year.

SDE = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

CR = Cumulative return, where the cumulation window extends from the month after announcement of quarter *t* earnings through the month of announcement of quarter *t*+1 earnings.

MVE = Market value of equity at the beginning the return cumulation window

Table 2: Replicating post-earnings announcement drift

Panel A: Fama-MacBeth regressions

$$CR_{t,t+1} = a + c_1 RSDE_t + c_2 RSDE_{t-1} + c_3 RSDE_{t-2} + c_4 RSDE_{t-3} + e_{t,t+1}$$

		<i>Intercept</i>	<i>RSDE_t</i>	<i>RSDE_{t-1}</i>	<i>RSDE_{t-2}</i>	<i>RSDE_{t-3}</i>	<i>Average R²</i>
(1)	<i>Estimate</i>	0.032	0.050	-0.003	-0.008	-0.015	0.021
	<i>t-statistic</i>	(3.30)	(11.75)	(-0.82)	(-1.99)	(-3.94)	
(2)	<i>Estimate</i>	0.031	0.047			-0.020	0.016
	<i>t-statistic</i>	(3.26)	(10.21)			(-4.73)	

N=110 regression coefficients from quarterly cross-sectional regressions

Panel B: Mishkin Analysis

$$SDE_{t+1} = a + b_1 SDE_t + b_2 SDE_{t-1} + b_3 SDE_{t-2} + b_4 SDE_{t-3} + e_{t+1}$$

$$CR_{t,t+1} = \phi_0 + \phi_1 [SDE_{t+1} - (a + b'_1 SDE_t + b'_2 SDE_{t-1} + b'_3 SDE_{t-2} + b'_4 SDE_{t-3})] + \gamma_{t,t+1}$$

<i>Predicted Sign</i>		(?)	(+)	(+)	(+)	(+)	(-)
		<i>Intercept</i>	<i>ERC</i>	<i>SDE_t</i>	<i>SDE_{t-1}</i>	<i>SDE_{t-2}</i>	<i>SDE_{t-3}</i>
<i>Earnings</i>	<i>Estimate</i>	0.228		0.429	0.129	0.074	-0.118
	<i>t-statistic</i>	(57.91)		(194.07)	(59.04)	(36.10)	(-61.78)
<i>Returns</i>	<i>Estimate</i>	0.038	0.029	0.230	0.114	0.088	-0.072
	<i>t-statistic</i>	(45.62)	(48.68)	(14.29)	(7.34)	(6.09)	(-5.30)
<i>Difference</i>				0.199	0.016	-0.014	-0.047
<i>Significant at 5%?*</i>				Y	N	N	Y

N=117,614 firm-quarter observations

Notes to Table 2. Table 2 reports results from replicating two key findings in the drift literature. Panel A reports results from Fama-MacBeth regressions. In Panel A, firms are sorted each quarter into *SDE* deciles, and *RSDE* is the firm's decile rank scaled to range from 0 to 1. This scaling procedure allows the coefficient to be interpreted as returns to a hedge portfolio formed by going long in firms in the top decile and going short in firms in the bottom decile. Inferences are based on the time-series distribution of cross-sectional regression coefficient estimates. Panel B reports results from nonlinear least squares estimation of the sequence of equations listed in Panel B.

Variable Definitions:

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

$RSDE$ = Decile rank of SDE , scaled to range from 0 to 1.

CR = Cumulative return, where the cumulation window extends from the month after announcement of quarter t earnings through the month of announcement of quarter $t+1$ earnings.

* This is a test of the constraint that the implied autocorrelation coefficient from the returns equation equals the autocorrelation coefficient from the earnings equation. The following test statistic is distributed asymptotically $\chi^2(1)$: $2n \log(SSR^c / SSR^u)$, where SSR^c is the residual sum of squares from estimating the system of equations with the constraint imposed while SSR^u is the residual sum of squares from estimating the system of equations without the constraint.

Table 3: The pricing kernel: Descriptive statistics and explanatory power for returns

Panel A: Descriptive statistics for the pricing kernel

	<i>N</i>	<i>Mean</i>	<i>STD</i>	<i>Q1</i>	<i>Median</i>	<i>Q3</i>
<i>Monthly time-series</i>	336	0.995	0.381	0.761	0.993	1.219
<i>Firm-quarter cumulative</i>	117,614	1.021	0.711	0.546	0.867	1.334

Panel B: The ability of the pricing kernel to explain returns

$$(CR_{t,t+1} - R_{t,t+1}^f) = a + d_1 m_{t,t+1} + d_2 MKT_{t,t+1} + d_3 SMB_{t,t+1} + d_4 HML_{t,t+1} + e_{t,t+1}$$

	<i>Intercept</i>	<i>m_{t,t+1}</i>	<i>MKT_{t,t+1}</i>	<i>SMB_{t,t+1}</i>	<i>HML_{t,t+1}</i>	<i>Avg R²</i>
(1) <i>Estimate</i>	0.074	-0.037				0.050
<i>t-statistic</i>	(32.14)	(-20.19)				
(2) <i>Estimate</i>	0.025		0.961			0.190
<i>t-statistic</i>	(29.30)		(48.59)			
(3) <i>Estimate</i>	0.036			0.838		0.092
<i>t-statistic</i>	(40.05)			(23.97)		
(4) <i>Estimate</i>	0.041				-0.369	0.044
<i>t-statistic</i>	(37.97)				(-12.20)	
(5) <i>Estimate</i>	0.020		0.969	0.501	0.368	0.287
<i>t-statistic</i>	(19.17)		(56.38)	(16.24)	(15.06)	
(6) <i>Estimate</i>	0.018	0.007	0.985			0.217
<i>t-statistic</i>	(7.35)	(3.46)	(46.29)			
(7) <i>Estimate</i>	0.072	-0.036		0.827		0.139
<i>t-statistic</i>	(32.47)	(-20.70)		(23.74)		
(8) <i>Estimate</i>	0.073	-0.033			-0.315	0.092
<i>t-statistic</i>	(32.34)	(-19.17)			(-10.53)	
(9) <i>Estimate</i>	0.018	0.001	0.977	0.496	0.367	0.310
<i>t-statistic</i>	(6.92)	(0.77)	(48.88)	(15.94)	(15.01)	
(10) <i>Estimate</i>	0.071	-0.035		0.818	-0.050	0.169
<i>t-statistic</i>	(32.44)	(-21.03)		(25.70)	(-2.15)	

N=839 firm-specific regression coefficients for all sample firms with 40 or more observations

Notes to Table 3. This table describes the distribution of the pricing kernel (Panel A) and the ability of the pricing kernel to explain the quarterly returns in the sample (Panel B). Panel B reports mean estimates and inferences from the cross-firm distribution of time-series regressions of the form in the equation in Panel B.

Variable Definitions:

$m_{t,t+1}$ = Pricing kernel, extracted from monthly returns to 20 industry sorted portfolios assuming the law of one price (see Appendix C).

CR = Cumulative return, where the cumulation window extends from the month after announcement of quarter t earnings through the month of announcement of quarter $t+1$ earnings.

R^f = 30-day T-bill rate cumulated over the window that begins the month after announcement of quarter t earnings and extends through the announcement of quarter $t+1$ earnings.

MKT , SMB , and HML = The Fama-French excess market, size, and book-to-market factors, respectively cumulated over the window that begins the month after announcement of quarter t earnings and extends through the announcement of quarter $t+1$ earnings.

Table 4: The relation between autocorrelation and future economic conditions

$$SDE_{t+1} = a + (b_{10} + b_{11} * UGDPgr)SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41} * UGDPgr)SDE_{t-3} + b_{50}UGDPgr + e_{t+1}$$

Predicted Sign		(?)	(+)	(?)	(+)	(+)	(-)	(?)	(?)	
UGDPgr				SDE _t *			SDE _{t-3} *			
Interval		INT	SDE _t	UGDPgr	SDE _{t-1}	SDE _{t-2}	SDE _{t-3}	UGDPgr	UGDPgr	R ²
<i>t,t+1</i>	<i>Estimate</i>	0.227	0.426	-0.958	0.130	0.074	-0.117	-0.385	3.969	0.397
	<i>t-statistic</i>	(56.09)	(189.27)	(-3.26)	(58.02)	(35.36)	(-59.80)	(-1.41)	(6.51)	
<i>t+1,t+2</i>	<i>Estimate</i>	0.226	0.427	1.245	0.130	0.074	-0.117	-0.127	0.780	0.397
	<i>t-statistic</i>	(55.74)	(189.23)	(4.19)	(58.01)	(35.26)	(-59.93)	(-0.46)	(1.29)	
<i>t+2,t+3</i>	<i>Estimate</i>	0.226	0.427	0.141	0.130	0.074	-0.117	0.143	1.003	0.397
	<i>t-statistic</i>	(55.73)	(188.95)	(0.48)	(58.03)	(35.29)	(-59.60)	(0.54)	(1.68)	
<i>t+3,t+4</i>	<i>Estimate</i>	0.224	0.427	0.237	0.130	0.074	-0.117	0.627	-3.387	0.397
	<i>t-statistic</i>	(55.08)	(189.03)	(0.79)	(58.03)	(35.28)	(-59.13)	(2.28)	(-5.53)	
<i>t+4,t+5</i>	<i>Estimate</i>	0.224	0.427	0.994	0.130	0.074	-0.117	0.661	-3.095	0.397
	<i>t-statistic</i>	(55.21)	(189.61)	(3.45)	(58.02)	(35.28)	(-59.43)	(2.47)	(-5.26)	
<i>t+5,t+6</i>	<i>Estimate</i>	0.224	0.427	1.303	0.130	0.074	-0.117	-0.471	-2.925	0.397
	<i>t-statistic</i>	(55.18)	(189.63)	(4.47)	(57.97)	(35.34)	(-59.79)	(-1.76)	(-4.97)	
<i>t+6,t+7</i>	<i>Estimate</i>	0.223	0.428	2.325	0.130	0.074	-0.118	-1.246	-2.858	0.397
	<i>t-statistic</i>	(55.08)	(189.84)	(7.84)	(58.00)	(35.36)	(-59.99)	(-4.57)	(-4.87)	
<i>t+7,t+8</i>	<i>Estimate</i>	0.224	0.427	0.574	0.130	0.074	-0.117	-0.567	-2.948	0.397
	<i>t-statistic</i>	(55.19)	(189.52)	(1.90)	(58.04)	(35.33)	(-59.88)	(-1.98)	(-5.02)	
<i>t,t+8</i>	<i>Estimate</i>	0.226	0.429	0.477	0.130	0.074	-0.118	-0.080	-0.053	0.397
	<i>t-statistic</i>	(55.47)	(188.93)	(6.80)	(57.96)	(35.31)	(-59.33)	(-1.25)	(-0.37)	

Notes to Table 4. Table 4 reports results from analyzing the relation between earnings autocorrelation and unexpected growth in seasonally-adjusted real GDP. Because the relation between earnings autocorrelation and the macroeconomy is not well-developed, I examine the association for several contemporaneous and future periods.

Variable Definitions:

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

$UGDPgr$ = Unexpected GDP growth.

I calculate growth in GDP ($GDPgr$) as current quarter GDP minus prior quarter GDP divided by prior quarter GDP. I use the following expectations model for one-period-ahead growth in GDP:

$$E(GDPgr_{t+1}) = .005 + .326 * GDPgr_t,$$

where the parameters are estimated using seasonally-adjusted real GDP data from the St. Louis Federal Reserve from 1954 through 2004. I iterate the expectations model for expectations more than one period ahead. For example, to estimate expected GDP growth two periods ahead, I use current GDP growth to estimate one-period-ahead GDP growth then enter the one-period-ahead GDP growth estimate into the model to estimate the two-period-ahead growth estimate. I calculate unexpected GDP growth as realized GDP growth minus the applicable GDP growth estimate.

Table 5. Systematic variation in autocorrelation of seasonally-differenced earnings

Panel A. Summary results from 110 quarterly cross-sectional regressions for 3 alternative index samples

$$SDE_{i,t+1} = a + b_{1,t+1}SDE_{i,t} + b_{2,t+1}SDE_{i,t-1} + b_{3,t+1}SDE_{i,t-2} + b_{4,t+1}SDE_{i,t-3} + e_{i,t+1}$$

Firm-specific index sample: all observations for firms with less than 40 observations

	<i>Mean</i>	<i>t-statistic</i>	<i>Q1</i>	<i>Median</i>	<i>Q3</i>
<i>Intercept</i>	0.213	13.79	0.131	0.198	0.313
<i>SDE_t</i>	0.411	48.84	0.352	0.416	0.481
<i>SDE_{t-1}</i>	0.128	20.19	0.089	0.123	0.171
<i>SDE_{t-2}</i>	0.084	15.45	0.052	0.079	0.108
<i>SDE_{t-3}</i>	-0.135	-25.98	-0.169	-0.133	-0.095

Extreme SDE_t index sample: all observations in the middle eight deciles of the *SDE_t* distribution

	<i>Mean</i>	<i>t-statistic</i>	<i>Q1</i>	<i>Median</i>	<i>Q3</i>
<i>Intercept</i>	0.160	9.81	0.071	0.136	0.232
<i>SDE_t</i>	0.574	53.85	0.502	0.585	0.659
<i>SDE_{t-1}</i>	0.082	18.65	0.050	0.079	0.109
<i>SDE_{t-2}</i>	0.058	13.32	0.028	0.051	0.083
<i>SDE_{t-3}</i>	-0.162	-35.54	-0.194	-0.160	-0.132

Extreme SDE_{t-3} index sample: all observations in the middle eight deciles of the *SDE_{t-3}* distribution

	<i>Mean</i>	<i>t-statistic</i>	<i>Q1</i>	<i>Median</i>	<i>Q3</i>
<i>Intercept</i>	0.189	11.23	0.106	0.185	0.264
<i>SDE_t</i>	0.405	53.48	0.355	0.413	0.454
<i>SDE_{t-1}</i>	0.122	24.32	0.089	0.121	0.158
<i>SDE_{t-2}</i>	0.077	14.92	0.048	0.071	0.102
<i>SDE_{t-3}</i>	-0.142	-17.43	-0.197	-0.143	-0.102

Table 5. Temporal variation in the autocorrelation of seasonally-differenced earnings

Panel B. The relation between autocorrelation coefficients and autocorrelation index

$$SDE_{t+1} = a + (b_{10} + b_{11}I_{t+1})SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41}I_{t+1})SDE_{t-3} + b_{50}I_{t+1} + b_{60}\hat{a}_{t+1} + e_{t+1}$$

	Predicted Sign	Firm-specific		Extreme SDE_t		Extreme SDE_{t-3}	
		(1)	(2)	Low (3)	High (4)	Low (5)	High (6)
INT	?	0.256 (24.93)	0.409 (24.16)	-0.417 (-17.24)	0.529 (15.24)	0.525 (32.41)	0.126 (4.72)
SDE_t	+	0.398 (54.54)	0.391 (53.08)	0.122 (16.93)	0.274 (32.19)	0.414 (58.81)	0.546 (93.92)
$SDE_t * I_{t+1}$	+		0.212 (2.23)	0.294 (3.02)	0.288 (2.70)	0.423 (3.17)	0.313 (3.26)
SDE_{t-1}	+	0.076 (14.25)	0.079 (14.85)	0.147 (25.56)	0.197 (28.61)	0.114 (18.45)	0.116 (20.21)
SDE_{t-2}	+	0.060 (15.20)	0.058 (13.93)	0.055 (9.29)	0.114 (15.36)	0.087 (17.89)	0.074 (15.42)
SDE_{t-3}	-	-0.208 (-45.37)	-0.202 (-40.11)	-0.127 (-23.03)	0.014 (1.90)	-0.134 (-35.49)	-0.075 (-13.23)
$SDE_{t-3} * I_{t+1}$	-		-0.343 (-4.05)	0.190 (2.68)	0.140 (1.75)	-0.205 (-2.33)	-0.067 (-0.63)
I_{t+1}	?		-0.008 (-0.05)	0.202 (0.66)	0.403 (0.90)	-0.411 (-1.26)	0.130 (0.26)
\hat{a}_{t+1}	+		0.628 (15.72)	1.099 (13.37)	1.009 (10.52)	0.867 (13.07)	0.986 (12.24)
R^2		0.384	0.510	0.153	0.387	0.426	0.682
Observations		839	839	11,143	10,980	11,240	10,744

Notes to Table 5. Table 5 reports results from analyzing the systematic temporal variation in earnings autocorrelation. Observations are assigned to a test subsample for each of three cuts of the data: (1) firms with at least 40 observations for estimating firm-specific SDE autoregressions, (2) extreme deciles of SDE_t each quarter, and (3) extreme deciles of SDE_{t-3} each quarter. For each of these three analyses, observations not assigned to the test subsample are assigned to the index subsample. Panel A reports results from quarterly cross-sectional SDE autoregressions for each of the three index subsamples. I use the time-series of first-order autocorrelation coefficients from Panel A as an ‘autocorrelation index,’ denoted I . Panel B reports results from estimating regressions that examine the relation between autocorrelation and the autocorrelation index for each of the test subsamples.

Variable Definitions:

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

I_{t+1} = Fiscal-quarter-mean-adjusted $b_{1,t+1}$ estimated with the corresponding index subsample (firm-specific, SDE_t , or SDE_{t-3}).

\hat{a}_{t+1} = Fiscal-quarter-mean-adjusted intercept estimated with the corresponding index subsample (firm-specific, SDE_t , or SDE_{t-3}).

Table 6. The association between autocorrelation and the pricing kernel

$$SDE_{t+1} = a + (b_{10} + b_{11}m_{t,t+1})SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + (b_{40} + b_{41}m_{t,t+1})SDE_{t-3} + b_{50}m_{t,t+1} + e_{t+1}$$

	Predicted Sign	Firm-Specific	Pooled	Extreme SDE_t		Extreme SDE_{t-3}	
		(1)	(2)	Low (3)	High (4)	Low (5)	High (6)
INT	?	0.246 (24.01)	0.226 (57.50)	-0.205 (-8.45)	0.368 (11.71)	0.469 (29.69)	0.063 (2.45)
SDE_t	+	0.409 (54.72)	0.429 (194.87)	0.235 (31.43)	0.345 (44.09)	0.419 (60.15)	0.517 (92.22)
$SDE_t * m_{t,t+1}$	-	-0.015 (-2.07)	-0.033 (-12.44)	-0.055 (-5.25)	-0.028 (-2.85)	-0.033 (-3.71)	-0.019 (-3.28)
SDE_{t-1}	+	0.075 (13.54)	0.129 (58.97)	0.131 (24.73)	0.163 (25.99)	0.116 (18.51)	0.115 (20.90)
SDE_{t-2}	+	0.057 (13.80)	0.074 (36.12)	0.058 (10.27)	0.099 (15.04)	0.082 (16.78)	0.075 (16.18)
SDE_{t-3}	-	-0.209 (-43.04)	-0.118 (-61.76)	-0.151 (-27.84)	-0.014 (-2.17)	-0.133 (-36.32)	-0.078 (-14.14)
$SDE_{t-3} * m_{t,t+1}$	+	-0.006 (-0.96)	0.002 (1.00)	-0.017 (-2.27)	0.008 (1.14)	0.007 (1.54)	-0.002 (-0.21)
$m_{t,t+1}$	+	0.057 (5.35)	0.048 (8.80)	-0.036 (-1.02)	0.016 (0.38)	0.049 (2.42)	0.041 (1.20)
R^2		0.425	0.400	0.19	0.388	0.428	0.674
Observations		839	117,614	10,655	10,198	11,098	10,378

Notes to Table 6. This table reports results from analyzing the association between the pricing kernel and SDE autocorrelation. The analysis is conducted at the firm-specific level, for the pooled sample, and for subsamples of observations in extreme deciles of SDE_t and SDE_{t-3} .

Variable Definitions:

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

$m_{t,t+1}$ denotes the pricing kernel, and it is extracted from monthly returns to 20 industry sorted portfolios as in Ahn, Conrad, and Dittmar [2003]. This variable is recast as deviations from the mean.

Table 7. Analysis of risk conditional on SDE

Panel A. Analysis of firm-specific excess returns

$$ExRet_{t,t+1} = \delta_0 + \delta_1 SDE_t + \delta_2 m_{t,t+1} + \delta_3 SDE_t * m_{t,t+1} + \delta_4 MKT_{t,t+1} + \delta_5 SMB_{t,t+1} + \delta_6 HML_{t,t+1} + \varepsilon_{t,t+1}$$

N=2,126 firm-specific regression estimates for firms with at least 60 monthly excess returns

Predicted Sign	(?)	(+)	(-)	(-)	(+)	(+)	(+)	Avg. R ²
	<i>Intercept</i>	<i>SDE_t</i>	<i>m_{t,t+1}</i>	<i>SDE_t*m_{t,t+1}</i>	<i>MKT_{t,t+1}</i>	<i>SMB_{t,t+1}</i>	<i>HML_{t,t+1}</i>	
<i>Estimate</i>	0.053		-0.043					0.044
<i>t-statistic</i>	(43.76)		(-37.80)					
<i>Estimate</i>	0.052	0.005	-0.042	-0.004				0.066
<i>t-statistic</i>	(40.10)	(6.56)	(-34.19)	(-5.51)				
<i>Estimate</i>	-0.005	0.003	0.008	-0.002	1.011	0.623	0.348	0.238
<i>t-statistic</i>	(-4.18)	(4.28)	(6.61)	(-3.06)	(82.08)	(39.55)	(21.38)	

Panel B. Analysis of monthly decile-portfolio excess returns

$$DecExRet_{t,t+1} = \delta_0 + \delta_1 RSDE_t + \delta_2 m_{t,t+1} + \delta_3 RSDE_t * m_{t,t+1} + \delta_4 MKT_{t,t+1} + \delta_5 SMB_{t,t+1} + \delta_6 HML_{t,t+1} + \varepsilon_{t,t+1}$$

N=3,290 decile-month excess returns

Predicted Sign	(?)	(+)	(-)	(-)	(+)	(+)	(+)	R ²
	<i>Intercept</i>	<i>RSDE_t</i>	<i>m_{t,t+1}</i>	<i>RSDE_t*m_{t,t+1}</i>	<i>MKT_{t,t+1}</i>	<i>SMB_{t,t+1}</i>	<i>HML_{t,t+1}</i>	
<i>Estimate</i>	0.003	0.014						0.007
<i>t-statistic</i>	(1.64)	(4.70)						
<i>Estimate</i>	0.063	0.014	-0.060					0.182
<i>t-statistic</i>	(22.97)	(5.18)	(-26.57)					
<i>Estimate</i>	0.054	0.031	-0.052	-0.018				0.184
<i>t-statistic</i>	(12.10)	(4.11)	(-12.22)	(-2.47)				
<i>Estimate</i>	-0.023	0.031	0.017	-0.018	1.048	0.606	0.339	0.858
<i>t-statistic</i>	(-11.43)	(9.83)	(9.26)	(-5.92)	(101.64)	(53.29)	(25.68)	

Notes to Table 7. Table 7 examines the role of the conditional risk adjustment implied by the autocorrelation risk model. Panel A reports results from firm-specific regression for all firms with at least 60 months of returns data. Panel B reports results for *SDE* decile returns in excess of the riskless rate.

Variable Definitions:

$ExRet_{t,t+1}$ = Firm's excess return for the month ending at $t+1$.

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

$m_{t,t+1}$ denotes the pricing kernel, and it is extracted from monthly returns to 20 industry sorted portfolios as in Ahn, Conrad, and Dittmar [2003].

MKT , SMB , and HML = The Fama-French excess market, size, and book-to-market factors, respectively.

$DecExRet_{t,t+1}$ = SDE decile portfolio return for month ending at $t+1$.

$RSDE$ is the decile rank of SDE, scaled to range from 0 to 1.

Table 8. Analysis of excess and size-adjusted returns for extreme SDE decile portfolios

$$\text{Return} = \alpha_{t+1} + \beta_{t+1}m_{t,t+1} + \varepsilon_{t,t+1}$$

N=329 decile-month returns for each extreme decile

Dependent

<i>Variable</i>	<i>SDE decile</i>		<i>Intercept</i>	<i>m_{t,t+1}</i>	<i>R²</i>
<i>Excess return</i>	<i>High</i>	<i>Estimate</i>	0.093	-0.072	0.246
		<i>t-statistic</i>	(12.48)	(-10.34)	
	<i>Low</i>	<i>Estimate</i>	0.060	-0.054	0.119
		<i>t-statistic</i>	(7.03)	(-6.66)	
<i>Size-adjusted Return</i>	<i>High</i>	<i>Estimate</i>	0.014	-0.005	0.010
		<i>t-statistic</i>	(4.36)	(-1.77)	
	<i>Low</i>	<i>Estimate</i>	-0.018	0.013	0.040
		<i>t-statistic</i>	(-4.92)	(3.69)	

Notes to Table 8. This table examines the adequacy of size-adjusted returns as a control for risk in extreme SDE decile portfolio returns.

Variable Definitions:

Excess Return = Decile portfolio return for month ending at $t+1$ in excess of the riskless return for the same period.

Size-adjusted Return = Decile portfolio return for month ending at $t+1$ using calculated using firms' size-adjusted returns.

$m_{t,t+1}$ denotes the pricing kernel, and it is extracted from monthly returns to 20 industry sorted portfolios as in Ahn, Conrad, and Dittmar [2003].

Table 9. Analysis of hedge portfolio returns

$$HedgeRet_{t,t+1} = \delta_0 + \delta_1 m_{t,t+1} + \delta_2 MKT_{t,t+1} + \delta_3 SMB_{t,t+1} + \delta_4 HML_{t,t+1} + \varepsilon_{t,t+1}$$

N=329 monthly hedge portfolio returns

<i>Predicted Sign</i>	(?)	(-)	(+)	(+)	(+)	R^2
	<i>Intercept</i>	$m_{t,t+1}$	$MKT_{t,t+1}$	$SMB_{t,t+1}$	$HML_{t,t+1}$	
<i>Estimate</i>	0.014					0.000
<i>t-statistic</i>	(7.46)					
<i>Estimate</i>	0.014		0.033			0.002
<i>t-statistic</i>	(7.31)		(0.80)			
<i>Estimate</i>	0.032	-0.018				0.039
<i>t-statistic</i>	(6.06)	(-3.66)				
<i>Estimate</i>	0.015		0.025	-0.348	-0.177	0.044
<i>t-statistic</i>	(8.29)		(0.56)	(-6.03)	(-2.66)	
<i>Estimate</i>	0.040	-0.024	-0.090	-0.353	-0.215	0.154
<i>t-statistic</i>	(6.65)	(-4.33)	(-1.76)	(-6.28)	(-3.29)	

Notes to Table 9. This table examines the ability of the pricing kernel to explain SDE hedge portfolio returns.

Variable Definitions:

HedgeRet = Return to the highest SDE decile portfolio minus the return to the lowest SDE decile portfolio for month $t+1$.

$m_{t,t+1}$ denotes the pricing kernel, and it is extracted from monthly returns to 20 industry sorted portfolios as in Ahn, Conrad, and Dittmar [2003].

MKT, *SMB*, and *HML* = The Fama-French excess market, size, and book-to-market factors, respectively.

Table 10. Mishkin analysis controlling for the interaction between SDE and the pricing kernel

$$SDE_{t+1} = a + b_{10}SDE_t + b_{20}SDE_{t-1} + b_{30}SDE_{t-2} + b_{40}SDE_{t-3} + e_{t+1}$$

$$CR_{t,t+1} = \phi_0 + \phi_1[SDE_{t+1} - (a + b'_{10}SDE_t + b'_{20}SDE_{t-1} + b'_{30}SDE_{t-2} + b'_{40}SDE_{t-3})]$$

$$+ (\phi_{20} + \phi_{21}SDE_t)m_{t,t+1} + \varepsilon_{t,t+1}$$

Predicted Sign		(?)	(+)	(+)	(+)	(+)	(-)	(-)	(-)
		<i>INT</i>	<i>ERC</i>	<i>SDE_t</i>	<i>SDE_{t-1}</i>	<i>SDE_{t-2}</i>	<i>SDE_{t-3}</i>	<i>m_{t,t+1}</i>	<i>SDE_t</i> <i>*m_{t,t+1}</i>
(1)	<i>Earnings</i>	<i>Estimate</i>	0.228	0.429	0.129	0.074	-0.118		
		<i>t-statistic</i>	(57.91)	(194.07)	(59.04)	(36.10)	(-61.78)		
	<i>Returns</i>	<i>Estimate</i>	0.038	0.029	0.230	0.114	0.088	-0.072	
		<i>t-statistic</i>	(45.62)	(48.68)	(14.29)	(7.34)	(6.09)	(-5.30)	
	<i>Difference</i>			0.199	0.016	-0.014	-0.047		
	<i>Significant at 5%?*</i>			Y	N	N	Y		
(2)	<i>Earnings</i>	<i>Estimate</i>	0.228	0.429	0.129	0.074	-0.118		
		<i>t-statistic</i>	(57.91)	(194.07)	(59.04)	(36.10)	(-61.78)		
	<i>Returns</i>	<i>Estimate</i>	0.038	0.030	0.235	0.123	0.092	-0.066	-0.030
		<i>t-statistic</i>	(46.10)	(49.34)	(14.87)	(8.07)	(6.40)	(-4.95)	(-26.82)
	<i>Difference</i>			0.194	0.007	-0.018	-0.052		
	<i>Significant at 5%?*</i>			Y	N	N	Y		
(3)	<i>Earnings</i>	<i>Estimate</i>	0.228	0.429	0.129	0.074	-0.118		
		<i>t-statistic</i>	(57.91)	(194.07)	(59.04)	(36.10)	(-61.78)		
	<i>Returns</i>	<i>Estimate</i>	0.038	0.030	0.234	0.123	0.092	-0.066	-0.029
		<i>t-statistic</i>	(45.98)	(49.09)	(14.70)	(8.07)	(6.41)	(-4.95)	(-26.04)
	<i>Difference</i>			0.195	0.006	-0.018	-0.052		
	<i>Significant at 5%?*</i>			Y	N	N	Y		

Notes to Table 10. This table reports results of nonlinear least squares estimation of the system of equations expressed above. The sample consists of 117,614 firm-quarter observations.

Variable Definitions:

$m_{t,t+1}$ denotes the pricing kernel, and it is extracted from monthly returns to 20 industry sorted portfolios as in Ahn, Conrad, and Dittmar [2003]. This variable is recast as deviations from the mean.

SDE_t = Current quarter earnings – earnings for the same quarter in the prior year, scaled by the time-series standard deviation of seasonal earnings changes for the prior eight quarters.

CR = Cumulative return, where the cumulation window extends from the month after announcement of quarter t earnings through the month of announcement of quarter t+1 earnings.

* This is a test of the constraint that the implied autocorrelation coefficient from the returns equation equals the autocorrelation coefficient from the earnings equation. The following test statistic is distributed asymptotically $\chi^2(1)$: $2n \log(SSR^c / SSR^u)$, where SSR^c is the residual sum of squares from estimating the system of equations with the constraint imposed while SSR^u is the residual sum of squares from estimating the system of equations without the constraint.