Reporting Bias and Economic Shocks*

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Abstract

We propose a parsimonious stochastic model of earnings that takes into account economic shocks and reporting bias. Our main prediction is that bias in reported earnings leads to a negative second lag autocorrelation in the residuals from a regression of current earnings on lagged earnings. This prediction allows us to create both a firm-level measure of earnings manipulation and a firm-level measure of the volatility of the operating environment. We find that the earnings manipulation measure is statistically significant for 22–25 percent of the firms with sufficient data on Compustat. Furthermore, traditional measures of accruals quality and earnings smoothing do not correlate with our measure. Several of the traditional measures do, however, vary monotonically with our firm-level measure of volatility, suggesting that they capture not only strategic biases, but also other stochastic properties of the firm's earnings process.

1 Introduction

How can a researcher identify firms that systematically manipulate earnings reports? How prevalent is misreporting? Given that economic performance is stochastic, these questions are not trivial. In the accounting literature, the traditional approach has been to construct a prediction model for earnings (or its components) and then to treat deviations from these

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predictions as evidence of either deliberate misrepresentation or low reporting quality. Two classic examples of this approach are Jones (1991) and Dechow and Dichev (2002). Jones (1991) develops a measure of accruals quality that assumes that non-discretionary accruals are a deterministic, linear function of the change in sales and the level of property, plant, and equipment, implying that anything unexplained by the model represents discretionary accruals. In a similar fashion, Dechow and Dichev (2002) specify a deterministic intertemporal decomposition of cash flows and then measure accruals quality as the estimation error in a regression of changes in working capital on past, current, and future cash flows from operations.

Although deterministic benchmarking measures are popular in empirical accounting research, as discussed by Dechow, Ge, and Schrand (2010), these measures have fundamental limitations. In essence, any deterministic benchmarking approach treats reporting bias as noise, thereby making it impossible to differentiate reporting bias from variation induced by the volatility of the firm's operating environment. Moreover, this inability to differentiate volatility from bias can lead to the excessive identification of earnings manipulation. To address this issue, we explore the time-series properties of reported earnings. We demonstrate that commonly assumed forms of bias in reported earnings produce serial correlation patterns in earnings surprises that are difficult to rationalize in the absence of misreporting. Specifically, we show that the residuals from a regression of reported earnings on lagged reported earnings will have a negative second lag autocorrelation in the presence of reporting bias. This result allows us to create a measure of the innovation in earnings and thereby evaluate the significance of reporting bias. We show that this autocorrelation-based measure of earnings manipulation is indeed orthogonal to the volatility of the firm's operating environment. This measure is therefore immediately useful as a substitute for the traditional measures, whenever volatility is a potential confounding factor. Moreover, our firm-level measure of volatility can be used as a complement to the traditional measures, because it allows researchers to separate operating volatility from reporting bias.

Throughout this study, we refer to misreporting as earnings manipulation. We view earnings manipulation as a broad concept that encompasses all forms of intertemporal shifting of earnings recognition aimed at (partially) masking performance shocks. These forms of intertemporal shifting can be broadly categorized into earnings smoothing and earnings manipulation. Earnings smoothing is akin to the precautionary savings of a household: the firm delays recognition of earnings in good years to build up a buffer that is subsequently used in a bad year. In the case of earnings management, the firm has no (or an insufficient) buffer to mask the current shock. It must therefore "borrow" from future earnings to report a desired number today. Both types of manipulation result in similar patterns of autocorrelation in earnings innovations. Because we pool these two types of misreporting, we use the broader term “earnings manipulation.”

To derive our main prediction, we make two assumptions: (1) earnings are persistent; and (2) the purpose of the bias is to mask the true shock. There are both economic and accounting-based explanations for the persistence in earnings. From the economic perspective, a performance shock to the firm rarely dissipates completely within a single year. Several structural reason lead to this delayed dissipation. For example, as discussed by Lerner (2002), patent protection of technological innovations typically lasts for multiple years. Other barriers to competition that determine industry structure (trade restrictions, increasing returns to scale, licenses,...) are also typically long-lived. Furthermore, commodity prices, interest rates, and wages are highly persistent (for discussions, see Cashin, Liang, and McDermott (1999) and Neely and Rapach (2008)). From the accounting perspective, financial reporting rules are designed to be conservative—gains are not recognized until they are verifiable or realized. This delayed recognition of gains leads firms to recognize positive performance shocks over multiple periods, thereby making accounting earnings even more persistent than economic profits.[1]

As pointed out by Fudenberg and Tirole (1995) and Trueman and Titman (1988), the bias

[1] The persistence of economic profits does not automatically translate into the persistence of accounting earnings. In principle, one could devise a system of financial reporting rules that accounts for the impact of every shock in present-value terms. Namely, all expected effects of the current shock to economic profits could be recognized in the current period, thereby leading to accounting earnings that are uncorrelated across periods. Such fair value accounting is not, however, the financial reporting system currently in place.

in reported earnings due to strategic manipulation is generally in the opposite direction from the performance shock. For example, under the typical earnings smoothing story, a manager under-reports earnings when performance shocks are favorable to create a precautionary buffer against future adverse shocks. This buffer produces a negative bias when shocks are positive and subsequently a positive bias when the manager takes advantage of the precautionary buffer. In the context of a typical earnings management story, the same prediction holds, except that the manager reports a desired number today at the expense of future earnings. Again, the bias is in the opposite direction from the performance shock.

We use these two assumptions to specify a parsimonious stochastic model of earnings that takes into account both economic shocks and reporting bias. The model implies that strategic manipulation leads to a negative second lag autocorrelation in the residuals from a regression of current earnings on lagged earnings. Furthermore, we show that this negative autocorrelation is difficult to rationalize in absence of reporting bias. Namely, in the absence of reporting bias, measurement error in accruals leads to positive second lag autocorrelation in the residuals as does delayed recognition of performance shocks driven by such factors as verifiability, conservatism, managerial procrastination, and adjustment costs. Empirically, we demonstrate that this negative autocorrelation appears in the data consistent with the analytical predictions and find that approximately 22–25 percent of firms with sufficient data on Compustat have significantly negative second lag autoregressive coefficients which are consistent with the systematic manipulation of reported earnings.

Next, we identify the period's innovation from the residuals to create a measure of idiosyncratic economic shocks. Consistent with the innovations representing economic shocks to firm performance, we find that they are negatively correlated with inflation and positively correlated with changes in GDP and short-term interest rates. Furthermore, we show that the idiosyncratic shocks are more correlated with these macroeconomic factors than are the lagged autocorrelated components of the residuals, which are driven by delayed recognition and reporting bias.

We then identify the firms for which the negative coefficient is most pronounced as the "suspects" of systematic earnings manipulation and examine whether traditional measures of accruals quality and earnings smoothing also identify these firms as suspect. We find that the traditional measures are uncorrelated with our measure. Furthermore, several of the traditional measures vary monotonically with the firm-level volatility of our idiosyncratic economic shocks, suggesting that the traditional measures capture not only strategic biases, but also other stochastic properties of the firm's earnings process, such as the volatility of supply and demand shocks. In contrast, we find no relation between our second lag autocorrelation estimates and the volatility of idiosyncratic economic shocks.

We acknowledge that our stylized model of earnings abstracts away from many factors that are likely to have important effects on earnings. Nevertheless, we believe that this simplification enables us to isolate both the stochastic process that drives earnings and the nature of commonly assumed forms of bias. In addition, this simplification provides us the necessary statistical power to identify earnings manipulation.

It is important to point out that this study is not about accruals quality and we do not provide a measure of accruals quality. Instead, our focus is on the *measurement* of the idiosyncratic economic shock that hits the firm. We use these shocks to filter out reporting bias and thereby recover "true" earnings, not the "true" accrual. In fact, our approach differs from traditional approaches that consider accruals as a mechanism used to smooth cash flow shocks. As we discuss earlier, these traditional approaches typically construct a "reasonable" benchmark of accruals based on other information reported by the firm, and then interpret deviations from the benchmark as reporting bias. In contrast to such deterministic benchmarking, we focus on the manipulation of earnings and are indifferent about whether manipulation occurs through accruals or cash flows. This can be either a strength or shortcoming of the model depending on the application. It is a strength in the sense that it allows researchers to identify overall earnings manipulation, both cash and accrual-based. It is a shortcoming in the sense that it does not allow researchers to study accruals manipulation separately from real earnings management.

It is also important to point out that there is a large accounting literature on the time series properties of annual earnings (for reviews of this literature, see Brown (1993) and Williams (1995); for examples, see Ball and Watts (1972), Brooks and Buckmaster (1976), Albrecht, Lookabill, and McKeown (1977), and Salamon and Smith (1977)). This literature primarily focuses on whether changes in the undeflated level of accounting income or changes in earnings per share are best described by either a random walk or a random walk with a drift. The primary application of this research is to produce estimates of earnings surprises for use in tests of the relation between earnings and stock returns (for applications, see Beaver, Lambert, and Morse (1980), Kormendi and Lipe (1987), and Collins and Kothari (1989)).

Although most of this prior research takes reported earnings at face value, several recent studies examine whether the time series properties of earnings can be used to identify earnings manipulation. For example, Fok and Franses (2009) find that fourth-quarter earnings have a much weaker autoregressive pattern than the earnings of the other three quarters. They interpret this result as the evidence of earnings management. In an earlier study, Hochberg, Newman, and Rierson (2004) point out that earnings management together with accrual reversals results in negative first-order autorcorrelation in accruals. While both of these results can indicate earnings management, they can also arise for reasons unrelated to misreporting. In particular, cash flow shocks can mechanically lead to autocorrelated accruals. For example, if today's cash flow is a function of today's sales, yesterday's accruals, and a random shock, then tomorrow's accruals will be affected by the same random shock through the beginning balance of payables and receivables, thereby resulting in autocorrelated accruals. Similarly, the weaker autocorrelation of fourth quarter earnings can arise simply because firms use the integral accounting method. Under the integral accounting method, firms allocate expenses over the first three quarters based on forecasted annual figures and then correct any forecast errors in the fourth quarter. These corrections imply that many of the performance shocks from the first three quarters are not recognized until the fourth quarter, thereby dampening the autocorrelation in fourth quarter earnings.

We contribute to the accounting literature by specifying a parsimonious stochastic model of earnings, which provides a benchmark of unmanipulated earnings. This benchmark allows us to create a measure of systematic earnings manipulation that we use to estimate the incidence of earnings manipulation among firms with sufficient data on Compustat. The incidence of earnings manipulation in the economy is relevant for researchers and policy makers who evaluate the efficacy of existing or proposed accounting standards and the reporting incentives arising from compensation and governance mechanisms. Although Burgstahler and Dichev (1997) and Myers, Myers, and Skinner (2007) provide some evidence on the possible incidence of earnings manipulation in the economy, there is limited academic research on this topic.[2]

We believe that an important application of our measure of manipulation would be to compare the incidence of earnings manipulation across countries, industries, and groups of firms. The same way we create the distribution of second lag autocorrelation coefficients for the US, one could create the distribution for any portfolio (country, industry, growth options...). Moreover, our measure can be used on a firm-level basis. For example, one could examine the association of our firm-level measure of manipulation with firm-level characteristics such as corporate governance, transparency, or equity incentives. Furthermore, the model allows researchers to measure firm-level idiosyncratic shocks. Such shocks can be used to estimate the volatility of a firm's operating environment, which is an important input for many corporate finance and asset pricing models. In addition, our volatility measure can be used as a control whenever traditional measures of earnings manipulation are used.

Finally, there are two caveats to this study. First, we identify the incidence as opposed to the intensity of earnings management. We believe that a promising extension to this study would be to explore the intensity dimension. However, this is not our current focus. Second, our method only captures systematic earnings manipulation that can be identified as

[2]We acknowledge that there is a large accounting literature on earnings manipulation. However, the bulk of this literature does not focus on incidence and instead focuses on topics such the link between earnings manipulation and incentives, compensation, and firm characteristics (for reviews, see Healy and Wahlen (1999), Dechow and Skinner (2000), and Dechow et al. (2010)).

a statistical regularity in the time series. We do not capture infrequent events such as large write downs of assets that include future expenses ("big baths").

2 Analytical framework

In this section, we analyze the statistical properties of a model in which idiosyncratic economic shocks drive the firm's performance as well as reporting choices. We then use these properties to specify tests of reporting quality.

As per prior research (for example, Richardson, Sloan, Soliman, and Tuna (2005)), we assume that firm i's actual economic performance follows an autoregressive process,

$$y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

in which $\beta_i > 0$ and $\varepsilon_{i,t}$ is an i.i.d. shock to the firm's performance. This specification captures the persistence in performance due to economic factors such as patent protections for technological innovations, barriers to competition, and the persistence of factors such as commodity prices, interest rates, and wages.

It is important to emphasize the nature of the shocks in our model. A common view in accounting is that accruals are a device that managers use to smooth cash flow shocks in order to provide a more accurate measure of firm performance (for discussions, see Dechow (1994) and Dechow, Kothari, and Watts (1998)). In contrast, the $\varepsilon_{i,t}$ shocks in our specification represent economic shocks. Some examples are changes in a firm's costs due to fluctuations in commodity prices and changes in sales due to fluctuations in demand. In the firm's financial statements a portion of these shocks appears as a cash flow shock and the remainder as an accrual. In contrast with much of the prior literature, the issues of decomposition are not important for our analysis because we do not model the components of earnings.

The major concern in estimating equation (1) is strategic bias. Namely, the variables in the regression are not directly observed and must therefore be inferred from the reported values.

From the statistical point of view, strategic bias differs from measurement error. Namely, it is correlated with the residuals and therefore biases the coefficients in an unpredictable manner. Our next step is to understand how the strategic bias specifically factors into equation (1).

We assume that true economic earnings must be inferred from the company's reports of cash flow, c_t, and change in working capital, $\triangle wc_t$, as follows:[3]

$$y_{i,t} = c_{i,t} + \triangle wc_{i,t}. \tag{2}$$

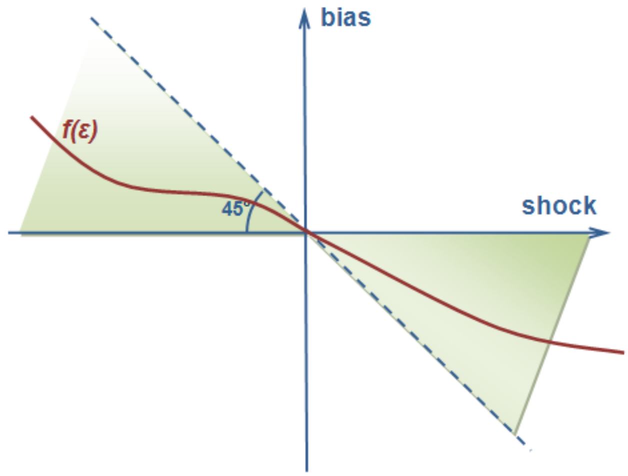
We assume throughout the analysis that only accruals are manipulated. We do not, however, rule out cash flow manipulation. In fact, to the extent that cash flow manipulation simply shifts cash flows across periods, it is analytically identical to accrual manipulation in our set up.

Wysocki (2009) points out that a common feature of most earnings management and smoothing stories is that the reporting bias goes in the direction opposite to the earnings shocks.[4] That is, in good times companies prefer to smooth out earnings reports by under-reporting current performance thereby transferring a portion of unexpected gains to future periods and in bad times companies use discretionary accruals to over-report current performance (for analytical examples, see Fudenberg and Tirole (1995) and Trueman and Titman (1988)). This feature also applies to situations in which managers try to meet targets such as bonus hurdles, analyst forecasts, and management forecasts. In these cases, the manager "borrows" from future earnings to report a desired number today. It is important to note that in our specification firms manipulate earnings in response to *idiosyncratic* shocks. In particular, this assumption is consistent with firms manipulating earnings upwards during economic

[3]This specification also applies to total accruals. In our empirical tests, we examine earnings that include both working capital and total accruals.

[4]A notable exception would be a large write down of assets that includes future expenses ("big bath"). Such a write down results in reporting bias that goes in the same direction as the firm's performance shock. Nevertheless, as discussed by Moehrle (2002), such a "big bath" creates reserves that are later used in a manner consistent with our specification: when future shocks are adverse, managers tap into the reserves to report satisfactory earnings. For a discussion of the link between earnings smoothing and "big baths," see Kirschenheiter and Melumad (2002).

Figure 1: Bias Function



boom. This would occur if the aggregate shock is positive, but the firm's idiosyncratic shock is negative.[5]

We formalize this observation by assuming that the manager's discretion in reporting the level of working capital, $d_{i,t}$, is a decreasing function of the period's economic shock, $d_{i,t} = f_i(\varepsilon_{i,t})$, where $f_i'(\varepsilon_{i,t}) \in (-1, 0)$. Figure 1 illustrates this assumption. The bias is a downward sloping curve with a slope between zero and negative one. The assumption $f_i'(\varepsilon_{i,t}) < 0$ implies that the strategic bias is in the opposite direction of the shock and $f_i'(\varepsilon_{i,t}) > -1$ implies that it is smaller in magnitude than the shock.[6] These assumptions have a clear economic interpretation: only a portion of the earnings surprise is transferred to subsequent periods. That is, the objective of the manager is to *decrease* the volatility of reported earnings.[7]

[5]A related example is the potential for overvalued equity to create pressure on managers to manipulate earnings (for discussions, see Jensen (2004) and Kothari, Loutskina, and Nikolaev (2009)). In this scenario, the manager observes a negative shock (or a sequence of negative shocks) relative to the market's beliefs. To the extent that the market's beliefs are based on past earnings realizations and other publicly available signals, our specification of bias holds.

[6]The assumption $f_i'(\varepsilon_{i,t}) < 0$ also implies that the bias is monotonically decreasing in the economic shock, which is not central to our analysis.

[7]Although the assumption about volatility-decreasing bias is intuitive, it is, however, restrictive in the following way. Namely, the current shock has no influence on the bias in future periods.

Under the assumptions described above, the observed level of working capital, $\tilde{wc}_{i,t}$ can be decomposed into a true portion, wc_t, and a discretionary portion, d_t:

$$\tilde{wc}_{i,t} = wc_{i,t} + d_{i,t} = wc_{i,t} + f_i(\varepsilon_{i,t}). \tag{3}$$

The period's observed accruals or change in working capital are therefore

$$\Delta \tilde{wc}_{i,t} = wc_{i,t} - wc_{i,t-1} + f_i(\varepsilon_{i,t}) - f_i(\varepsilon_{i,t-1}). \tag{4}$$

This specification allows equation (1) to be rewritten in terms of the observable variables and economic shocks. The equation remains unchanged, but the noise term no longer has the interpretation of the current period economic shock. The structure of accruals specified by equation (4) implies that (1) can be written as

$$\tilde{y}_{i,t} = \alpha_i + \beta_i \tilde{y}_{i,t-1} + \tilde{\epsilon}_{i,t}, \tag{5}$$

in which the structural error term, $\tilde{\epsilon}_{i,t}$, takes the following form:

$$\tilde{\epsilon}_{i,t} = \varepsilon_{i,t} + f_i(\varepsilon_{i,t}) - (1+\beta_i) f_i(\varepsilon_{it-1}) + \beta_i f_i(\varepsilon_{i,t-2}). \tag{6}$$

As shown in the Appendix, this result follows immediately once $\tilde{wc}_{i,t}$ is expressed as per equation (3) and substituted into (2). If $f_i(\varepsilon_{i,t})$ is a linear function, then reported earnings follow an ARMA(1,2) process with a negative coefficient on the second lag of the moving average.[8]

It is straightforward to verify from equation (6) that the structural errors in the model with strategic reporting are autocorrelated, with the sign of the first lag autocovariance being ambiguous and the sign of the second lag autocovariance always negative in the presence of

[8] Prior research examines which ARIMA model best describes and forecasts the earnings process (for discussions, see Brown (1993) and Williams (1995)). This research, however, studies reported earnings and therefore has little to say about either the statistical properties of true earnings or the implications of reporting bias.

strategic reporting.[9] The first two autocovariances are

$$
\begin{aligned}
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) &= -(1+\beta_i)\left(cov\left[\varepsilon_{i,t-1} + f_i(\varepsilon_{i,t-1}), f_i(\varepsilon_{i,t-1})\right] + \beta_i var\left[f_i(\varepsilon_{i,t-2})\right]\right), \\
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-2}) &= \beta_i cov\left[\varepsilon_{i,t-2} + f_i(\varepsilon_{i,t-2}), f_i(\varepsilon_{i,t-2})\right].
\end{aligned}
$$

The sign of the first lag autocovariance is ambiguous, because the expression includes both a negative and a positive term.[10] Depending on the functional form of $f_i(\varepsilon_{i,t})$, either the negative or the positive term can dominate. In contrast, the second lag autocovariance is always negative.

Mechanics of the results Two assumptions underpin our model. First, we assume that the reporting bias is counter-cyclical (i.e., aimed at smoothing the reported performance) and that it reverses in the next period. Second, we assume that true earnings follow an AR(1) process. The first assumption—bias reversal—implies that every period's reported earnings contains the current period's bias, as well as the previous period's bias, with the previous period's bias entering the current report with the opposite sign. The second assumption—the autoregressive nature of earnings—introduces the biases from the last period report, as well as the bias from the last period's shock. The shock of the last period partially cancels out with the two components containing the last period bias. It is therefore unclear how the last period's shock affects current reported earnings, whereas the shock from two periods prior manifests itself only through the bias in the autoregressive components with the opposite sign. This generates negative second lag autocorrelation in the residuals.

Alternative explanations Our result implies that a current favorable shock to the firm's performance will have in expectation a negative impact on reported earnings two periods into the future. This is in sharp contrast with the implications of other commonly proposed

[9] For the derivations, see the Appendix.

[10] To see why the first term is negative, note the following: $f_i'(\varepsilon_{i,t}) \in (-1, 0)$, therefore $\varepsilon_{i,t} + f_i(\varepsilon_{i,t})$ is increasing in $\varepsilon_{i,t}$. Because $f_i(\varepsilon_{i,t})$ is decreasing in $\varepsilon_{i,t}$, the covariance of $\epsilon_{i,t} + f_i(\epsilon_{i,t})$ and $f_i(\epsilon_{i,t})$ is always negative.

explanations for the persistence in earnings shocks (delayed recognition, conservatism, managerial procrastination, adjustment costs, persistence of performance shocks...). All of these factors imply that the current favorable shock will positively affect future earnings. Statistically, they imply that earnings follow a moving average process with positive coefficients (for an example of delayed recognition and how it relates to accounting conservatism, see the Appendix). If one believes that these factors drive the persistence in shocks to earnings, then one should expect positive autocorrelations in the residuals thereby making our empirical findings even more perplexing.

Conceptually, the main difference between reporting bias and delayed recognition is that bias affects the observed statistical relationship between past and present earnings, and can therefore be thought of as a measurement discrepancy. In contrast, delayed recognition changes the true statistical relationship between past and present earnings, and therefore results in a different statistical outcome. Nevertheless, delayed recognition can be an appealing, but misleading, parallel when one thinks about bias. If "true" earnings correspond to the timely recognition of every performance shock at its present value, then recognition delays are analogous to a reporting bias. Note, however, that under this definition, there can be no persistence in "true" earnings, because all future effects of the shock are captured by construction in the current earnings report. That is, present-value accounting cannot generate autoregressive earnings. Under present-value accounting, "true" earnings must follow a random walk and our analytical results would not hold. Put differently, present value accounting and AR(1) are mutually exclusive. It is the current value nature of generally accepted accounting principles that makes earnings persistent. This observation, along with the persistence in performance shocks and the gradual dissipation of economic rents due to competitive pressures justify the AR(1) assumption.

Linear smoothing It is instructive to consider the special case in which the reporting bias is a linear function of the shock, $f_i(\varepsilon_{i,t}) = -\delta\varepsilon_{i,t}$, $0 < \delta < 1$. Let $var(\varepsilon_{i,t}) = \sigma_\varepsilon^2$. In this case,

$$
\begin{aligned}
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) &= (1+\beta_i)\delta\,(1-(1+\beta_i)\,\delta)\,\sigma_\varepsilon^2, \\
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-2}) &= -\beta_i\delta(1-\delta)\sigma_\varepsilon^2.
\end{aligned}
$$

The sign of the first lag autocovariance depends on how the aggressiveness of smoothing, δ, compares to $1/(1+\beta_i)$. When δ is low, which corresponds to less aggressive smoothing, the first lag autocovariance is positive. As aggressiveness increases (i.e. δ increases), the first lag autocovariance decreases. Mathematically, if $\delta > 1/(1+\beta_i)$, then $cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) < 0$, and if $\delta < 1/(1+\beta_i)$, then $cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) > 0$. In contrast, the second lag autocovariance is always negative and its minimum is achieved at $\delta = 1/2$, which corresponds to half of the current shock being transferred to the future period.

Working capital measured with noise It is also worth considering the case in which the level of working capital is measured with noise in the absence of strategic bias. Random mismeasurement that is independent of economic shocks leads to autocorrelation patterns different from those predicted by strategic reporting. Just as with reporting bias, we assume that the measurement error distorts the end-of-year balance of working capital, $w\tilde{c}_{i,t} = wc_{i,t} + v_{i,t}$, in which $v_{i,t}$ is the measurement error. Under this assumption, the structural error term is

$$
\tilde{\epsilon}_{i,t} = \varepsilon_{i,t} + v_{i,t} - (1+\beta_i)v_{i,t-1} + \beta_i v_{i,t-2}. \tag{7}
$$

(For a derivation of the structural error term and the autocovariances when the level of working capital is measured with noise, see the Appendix). If we assume that $v_{i,t}$ is i.i.d. with variance σ_v^2, then the first and second lag autocovariances are as follows:

$$
\begin{aligned}
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) &= -(1+\beta_i)^2\sigma_v^2, \\
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-2}) &= \beta_i\sigma_v^2.
\end{aligned}
$$

The first lag autocovariance is always negative, while the second lag autocovariance is always positive.

Both the measurement error and strategic bias specifications predict autoregressive patterns in the structural errors. However, the signs of the autocovariances predicted by these two specifications are quite different. In the subsequent empirical analysis, we examine which one is supported by the data.

3 Empirical tests

In this section, we empirically test the analytical predictions of the model. On a firm-level basis, we estimate equation (4) for earnings before long term accruals and earnings before extraordinary items and then examine the time series properties of the residuals. Next, we show that our measure of firm-level economic shocks correlates with macroeconomic factors. Finally, we investigate how our measures of manipulation and economic shocks correlate with traditional measures of accruals quality and earnings smoothing.

3.1 Sample

Table 1 presents the derivation of our sample. It starts with US firms that report their financial statement under SFAS 95, and therefore begins in 1988 and ends in 2008. This requirement leads to 97,017 firm years on the Compustat Fundamental Annual File with non-missing cash flow from operations (Compustat $OANCF$), earnings before extraordinary items (Compustat IB), total assets (Compustat AT), lagged total assets, change in accounts receivable (Compustat $RECCH$), and change in inventory (Compustat $INVCH$). To minimize the effect of extreme observations, we truncate the 1st and 99th percentiles of earnings before long term accruals, lagged earnings before long term accruals, earning before extraordinary items, and lagged earnings before extraordinary items. Finally, we require that each firm in the sample have at least 15 annual observations leading to the final sample of 1,664 firms with 29,185 firm years.[11] Our requirements are similar to those used by Dechow and Dichev (2002) and Wysocki (2009), who present similar sample sizes.

[11]Results are similar if we require either a minimum of 12 or 18 annual observations.

3.2 Descriptive statistics

Table 2 presents descriptive statistics for the measures used in the empirical analyses. We deflate all measures by lagged total assets. Following Hribar and Collins (2002), we estimate cash flow from operations, $\tilde{c}_{i,t}$, by subtracting cash flow related to extraordinary items and discontinued operations (Compustat $XIDOC$) from cash flow from operations (Compustat $OANCF$).[12] In the empirical analyses, we use two measures of earnings. First, we calculate the observed change in working capital, $\triangle\tilde{wc}_{i,t}$, using the method described in Dechow and Dichev (2002)

$$\triangle\tilde{wc}_{i,t} = -1 * (RECCH + INVCH + APALCH + TXACH + AOLOCH). \tag{8}$$

We then create our first measure, earnings before long term accruals, $\tilde{e}_{i,t} = \tilde{c}_{i,t} + \triangle\tilde{wc}_{i,t}$. For our second measure, we use earnings before extraordinary items $\tilde{ib}_{i,t}$ (Compustat IB), which includes long term accruals such as depreciation and deferred taxes. The distributions of our empirical measures are similar to those presented in both Dechow and Dichev (2002) and Wysocki (2009).

3.3 Estimation

For each firm in the sample, we estimate the following two specifications using Stata's ARIMA function

$$\tilde{e}_{i,t} = \alpha_i + \beta_i \tilde{e}_{i,t-1} + \tilde{\epsilon}_{i,t} \tag{9}$$

$$\tilde{ib}_{i,t} = \alpha_i + \beta_i \tilde{ib}_{i,t-1} + \tilde{\epsilon}_{i,t} \tag{10}$$

[12] We obtain similar results if we do not subtract cash flow related to extraordinary items and discontinued operations.

in which the structural error term follows $\tilde{\epsilon}_{i,t}$ an AR(2) process

$$\tilde{\epsilon}_{i,t} = \rho_{i,1}\tilde{\epsilon}_{i,t-1} + \rho_{i,2}\tilde{\epsilon}_{i,t-2} + \varepsilon_{i,t}$$

with $\varepsilon_{i,t}$ representing an idiosyncratic shock to the firm's performance. We allow the structural error terms to follow an AR(2) process because our empirical predictions are about the second lag autocovariances of the structural errors, not the coefficients on the idiosyncratic economic shocks.[13]

Of the 1,664 firms in the sample, five do not converge for earnings before long term accruals and 25 do not converge for earnings before extraordinary items. Table 3 presents the coefficient estimates for equations (9) and (10). Mean and median coefficients on prior earnings are in the 0.4–0.6 range (0.533 and 0.641, for earnings before long term accruals; 0.426 and 0.517, for earnings before extraordinary items).[14]

We next examine the model's predictions about the autocorrelations of the residuals. Table 4 presents the estimates of the first and second lag coefficients of the residuals from equations (9) and (10). These coefficients represent the partial autocorrelations of the structural residuals, that purge the estimates of the indirect correlations in the process.[15] The mean and median first lag coefficient estimates are positive (0.107 and 0.065, for earnings before long term accruals; 0.116 and 0.070, for earning before extraordinary items) and the means and medians are significantly positive.

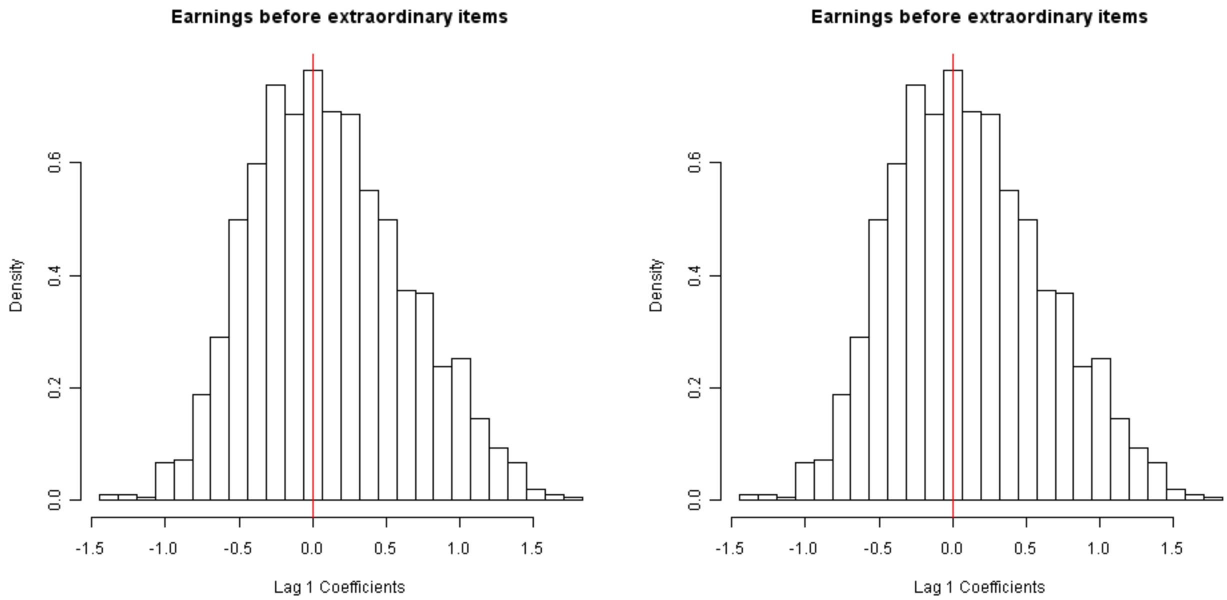
In contrast, and consistent with the analytical predictions, the mean and median estimates

[13] An alternative approach would be to estimate a model in which the structural errors follow an MA(2) process and then use the estimated coefficients to calculate the autocovariances. This approach would, however, require us to make strong assumptions about the distribution of the idiosyncratic shocks, namely normality, which is unlikely given the nature of earnings and the fact that equation (6) potentially includes non-linear transformations of the shocks. Furthermore, maximum likelihood estimates of moving average parameters are unstable for short time series. For a discussion of the issues related to estimating moving average models, see Hamilton (1994).

[14] These firm-specific estimates are similar in magnitude to those presented by prior research that estimates persistence based on quintiles (for example, Dechow and Dichev (2002) and Dichev and Tang (2009)). Under reporting bias, these coefficient estimates are, however, both biased and inconsistent, because $cov(\tilde{ib}_{i,t-1}, \tilde{\epsilon}_{it})$ and $cov(\tilde{\epsilon}_{i,t-1}, \tilde{\epsilon}_{i,t})$ would not be equal to zero.

[15] For example, a correlation between $\tilde{\epsilon}_{i,t}$ and $\tilde{\epsilon}_{i,t-2}$ arises solely for the reason that they are both correlated with $\tilde{\epsilon}_{i,t-1}$.

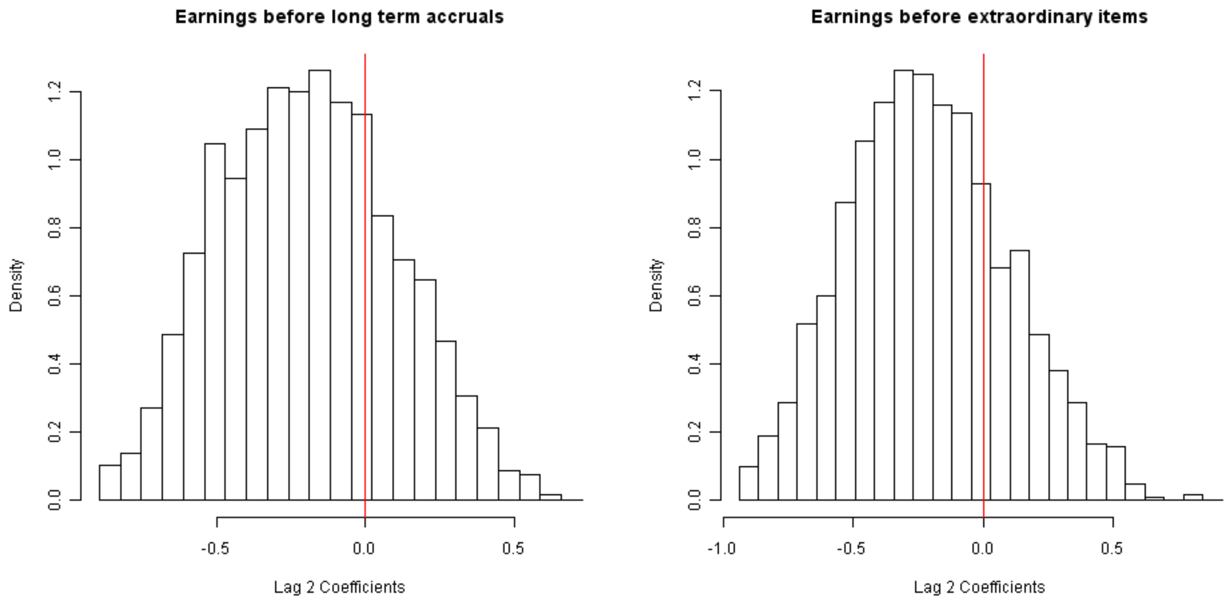
Figure 2: Distribution of first lag coefficient estimates



for the second lag coefficients are negative (-0.193 and -0.198, for earnings before long term accruals; -0.212 and -0.229, for earnings before extraordinary items). As shown in Table 4, 22–25 percent of the estimates are significantly negative, while few of the estimates are significantly positive (two percent for earnings before long term accruals; three percent for earnings before extraordinary items).[16] As a benchmark to gauge significance of the second lag coefficients, we simulated earnings processes that involve no reporting bias and zero autocorrelation in the residuals. For the simulations, we found that approximately five percent of the coefficients were statistically significant. While we attribute the difference between the 22–25 percent in our sample and the five percent under the zero bias simulations to manipulation, we do not believe it is fair to argue that 17–20 percent of the firms in the economy manipulate earnings. Rather, one should think of the estimates as lower bounds given that we lack statistical power due to the short time series we use in the estimations. Moreover, in the simulations we assume

[16]Small sample bias is a potential reason for the coefficient estimates to be negative (for a discussion, see Kendall (1954)). Nevertheless, even after taking into account small sample bias, the distributions of second lag coefficient estimates are shifted in the negative direction. For example, assuming zero autocorrelations, bias is $-1/n$, which is -0.055 for the median firm in the sample.

Figure 3: Distribution of second lag coefficient estimates



zero autocorrelation in the residuals. As we discuss in Section 2, there are many reasons to believe that in the real data the residuals should be positively autocorrelated. Such positive autocorrelation would suggest that the five percent estimate is an upper bound.

Figure 3 graphically summarizes this study's main message, which is two-fold. First, strategic bias can be identified in the autoregressive patterns of the earnings regression residuals. Second, the magnitude, the statistical significance indicator, or the percentile of the second lag autocorrelation coefficient can all be used as firm-level measures of earnings manipulation, which, as we discuss in Section 3.6, are orthogonal to operating volatility.

3.4 Economic shocks and macroeconomic factors

To verify that earnings shocks are indeed driven by economic factors, we now examine whether our measure of idiosyncratic economic shocks correlates with three macroeconomic factors: the annual percentage change in GDP; inflation as measured by the GDP deflator; and the annual change in the one year Treasury rate. We obtain GDP from the website of the Federal

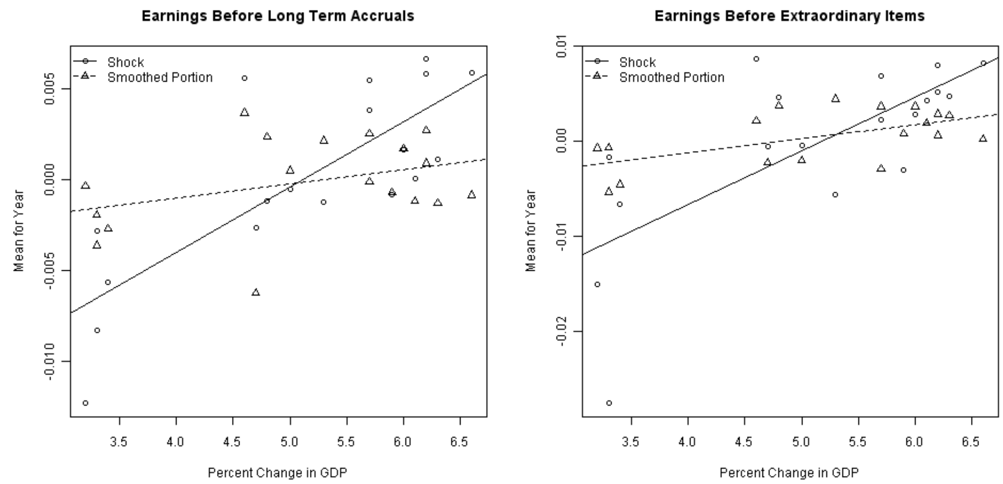
Reserve Bank of St. Louis, the GDP deflator from GPO Access, and the one year Treasury rates from the Federal Reserve Board's website. In addition to macroeconomic factors, the idiosyncratic economic shocks likely include firm- and industry-level factors. We do not include firm and industry-level returns in our analysis, because they conflate idiosyncratic shocks with the output of the accounting system. We calculate our firm-level measure of idiosyncratic economic shocks, $\varepsilon_{i,t}$, as the period's innovation from the estimation of equations (9) and (10).

Table 5 presents ordinary least squares regressions in which the dependent variables are the $\varepsilon_{i,t}$'s for earnings before long term accruals and earnings before extraordinary items. We cluster the standard errors at the annual level. Consistent with the analytical predictions that earnings shocks are driven by economic factors, we find that GDP and the change in one year Treasury rate are all positively and significantly associated with both of the economic shock measures. Furthermore, inflation is negatively and significantly associated with the economic shock based on earnings before long term accruals.

To benchmark these correlations, we next examine the extent that the lagged autocorrelated component of the structural residual is associated with the macroeconomic factors. This component contains autocorrelations due to both reporting bias and delayed recognition of past shocks. Our approach suggests that the association of this component with current macroeconomic variables should be weaker than that of the economic shock variable $\varepsilon_{i,t}$. We find that the data support this intuition. Table 6 presents ordinary least squares regressions in which the dependent variables are the $\rho_{i,1}\epsilon_{i,t-1} + \rho_{i,2}\epsilon_{i,t-2}$'s for earnings before long term accruals and earnings before extraordinary items. As per the prior table, we cluster the standard errors at the annual level. Compared to the shock measure, the autocorrelated component is either uncorrelated or less correlated with the macroeconomic factors than the economic shock. Furthermore, the explanatory power for these regressions is less than that of the regressions presented in Table 5 and p values for the overall fit of several of the regressions presented in Table 6 are not significant at conventional levels.

Although the coefficients are statistically significant in the predicted directions for the id-

Figure 4: Relations between mean annual shocks, mean annual smoothed portions, and GDP



iosyncratic shock regressions, the adjusted R^2s are less than one percent. The low adjusted R^2s are consistent with the tremendous firm-level heterogeneity that the industrial organization literature finds with respect to productivity and responses to changes in unemployment (for discussions, see Davis and Haltiwanger (1992) and Syverson (2004)). Consistent with firm-level heterogeneity, in untabulated tests we find that the adjusted R^2s increase when we run the shock regressions within industry and when we partition the sample on total assets.

Despite this firm-level heterogeneity, our measure on average captures macroeconomic shocks. For example, Figure 4 compares the relations between the mean annual shock and the percent change in GDP with the relations between the mean annual smoothed portion and the percent change in GDP. As per the regressions presented in Tables 7 and 8, the mean annual shocks are more correlated with the percent change in GDP than the mean annual smoothed portions of the residuals, which include autocorrelations due to delayed recognition and reporting bias. Moreover, in untabulated tests we find that the adjusted R^2s for models in which the shocks are the dependent variable are higher than when we use deflated earnings as the dependent variable.

3.5 Accruals quality and earnings smoothing measures

There are several measures of accruals quality and earnings smoothing that are often used in accounting research. We now examine how our manipulation measure compares with these traditional measures. Two approaches are commonly used in the accounting literature to evaluate accruals quality. Jones (1991) develops a measure of accruals quality that assumes that non-discretionary accruals are a linear function of the change in sales and the level of property, plant, and equipment, implying that anything unexplained by the model represents discretionary accruals. For our empirical tests, we therefore calculate $Jones_i$ as one minus the R^2 from a firm-level modified Jones model.

Dechow and Dichev (2002) propose an approach for estimating accrual quality based on the argument that accruals inter-temporally shift cash flow recognition. Hence, they assume a deterministic intertemporal decomposition of cash flows and then measure accruals quality as the estimation error in a regression of changes in working capital on past, current, and future cash flows from operations. They interpret higher standard deviations of the residuals as lower quality accruals. Our second accruals quality measure, $DechowDichev_i$, is negative one times the standard deviation of the residuals from the regression of the change in working capital on lagged, current, and future cash flow from operations. We multiply by negative one so that, consistent with the other measures, accruals quality increases in their measure.

In addition to the two above mentioned measures of accruals quality, two *ad hoc* measures are commonly used to identify earnings smoothing (for an in depth discussion of these measures, see Dechow et al. (2010)). The first smoothing measure, $Ratio_i$, is the ratio of the standard deviation of earnings before extraordinary items to the standard deviation of the cash flow from operations. The intuition behind this measure is that the goal of intentional smoothing is to remove cash flow shocks from reported earnings. Therefore, intentional smoothing should lead to lower volatility in reported earnings than in cash flows, implying that the measure decreases in smoothing. The second smoothing measure, $Correlation_i$, is the Spearman rank correlation between the change in cash flow from operations and the change in working capital accruals. Similar to the first measure, the intuition behind this measure is that a more negative correlation indicates that managers use accruals to smooth shocks to cash flows, implying that the measure decreases in smoothing.

Table 7 presents descriptive statistics and correlations for the firm-level accruals quality and earning smoothing measures. To be consistent, we specify each measure so that it decreases in smoothing. Similar to Dechow et al. (2010), we find that the traditional measures are somewhat correlated among themselves. For example, the correlation between $Correlation_i$ and $Ratio_i$ is 0.388, the correlation between $Correlation_i$ and $DechowDichev_i$ is -0.207, the correlation between $Ratio_i$ and $DechowDichev_i$ is -0.249, and the correlation between $Jones_i$ and $DechowDichev_i$ is 0.046, implying that except for $Jones_i$ the measures pick up similar factors. We next investigate the extent that these measures are associated with the second lag autocorrelation.

Table 8 Panels A and B tabulate the traditional measures by the deciles of the second lag coefficient estimates. None of the traditional measures vary systematically with the deciles of the second lag coefficient estimates for either of the earnings measures. In untabulated tests, we examined the correlation between the traditional measures and the second lag coefficient estimates. Of the four traditional measures, only $Correlation_i$ is significantly associated with the second lag coefficient (-0.060, for earning before long term accruals; -0.045, for earnings before extraordinary items). Furthermore, we compared the means and medians of the traditional measures based on whether the firm's second lag coefficient estimate is negative and significantly different from zero, and found no significant differences for any of the traditional measures.

Overall, we find that our measure of strategic bias is not associated with the traditional measures of accruals quality and earnings smoothing, implying that the traditional measures and our measure capture different properties of reported earnings. In the next section, we investigate a potential reason for why the measures are not associated.

3.6 Volatility of idiosyncratic economic shocks

As shown by Dechow, Sloan, and Sweeney (1995) and Hribar and Nichols (2007), the traditional measures of accruals quality and earnings smoothing can capture not only strategic biases, but also other stochastic properties of the firm's earnings process, such as the volatility of supply and demand shocks. Furthermore, our second lag coefficient estimate is open to the same criticism. We therefore examine the associations of the traditional measures and our second lag estimates with our estimates of the volatilities of the firm-level idiosyncratic economic shocks. We create two volatility measures that are the firm-level standard deviations of the idiosyncratic shocks, $\varepsilon_{i,t}$, based on earnings before long term accruals and earnings before extraordinary items.

Table 9 Panels A and B present deciles of the firm-level volatility measures then tabulate by volatility decile the means for each of the traditional measures and our second lag estimates. Consistent with the traditional measures capturing the stochastic properties of the earnings process, $Correlation_i$ and $Ratio_i$ increase almost monotonically and $DechowDichev_i$ decreases monotonically in the volatility deciles for both earnings measures. In contrast, we find no relation between the volatility deciles and our estimates of the second lag autocorrelation.

In untabulated tests, we find similar results when we examine correlations between the volatility measures, the second lag estimates, and the traditional measures of accruals quality and earnings smoothing. $Correlation_i$, $Ratio_i$, and $DechowDichev_i$ are all significantly correlated with the volatility estimates (0.438, 0.221, and -0.754, for earnings before long term accruals; 0.387, 0.490, and -0.698, for earnings before extraordinary items). Once again, the second lag autocorrelation estimates are not significantly correlated with the volatility estimates (-0.013, for earnings before long term accruals; 0.037, for earnings before extraordinary items).

The strong associations of the traditional measures with our measure of volatility imply either that the traditional measures are in fact capturing earnings volatility or that the dimension of earnings manipulation captured by these measures is strongly associated with the volatility of the operating environment.

4 Conclusion

We contribute to the accounting literature by providing a parsimonious stochastic model of earnings that identifies earnings manipulation and idiosyncratic economic shocks. We use this model to formulate an empirical strategy to identify firms that systematically manipulate earnings and estimate the prevalence of earnings manipulation in the US economy. Furthermore, we show that traditional measures of accruals quality and earnings smoothing do not correlate with our measure of manipulation. In fact, several of the traditional measures vary monotonically with our firm-level measure of the volatility of idiosyncratic economic shocks, suggesting that the traditional measures capture not only strategic biases, but also other stochastic properties of the firm's earnings process. To mitigate these problems of the traditional measures, researchers can use our volatility measure to control for the stochastic properties of the underlying earnings process.

This study is, however, subject to several caveats. First, we focus on the manipulation of earnings and are indifferent about whether manipulation occurs through accruals or cash flows. Hence, our approach is not about accruals quality and we do not provide a measure of accruals quality. Instead, we focus on measuring the idiosyncratic economic shock that hits the firm, not on measuring the "true" accrual. Second, our approach captures the incidence as opposed to the intensity of earnings management. Third, we are only able to capture systematic earnings manipulation that can be identified as a statistical regularity in the time series. We do not capture infrequent events such as "big baths."

In conclusion, we believe that there are two promising extensions to this study. The first would be to better understand and provide a theoretical foundation for the functional form of the strategic bias, $f_i(\varepsilon_{i,t})$. The second extension would be to study empirically how specific accruals, such as inventory and receivables, respond to economic shocks over the financial reporting cycle. These extensions would allow future research to estimate the intensity, in addition to the incidence, of earnings manipulation.

Appendix

Error term under strategic bias

$$\begin{aligned}\tilde{y}_{i,t} &= c_{i,t} + \Delta \tilde{w} c_{i,t} \\ &= c_{i,t} + wc_{i,t} + f_i(\varepsilon_{i,t}) - wc_{i,t-1} - f_i(\varepsilon_{i,t-1}) \\ &= c_{i,t} + \Delta wc_{i,t} + f_i(\varepsilon_{i,t}) - f_i(\varepsilon_{i,t-1})\end{aligned}$$

$$\begin{aligned}\tilde{\epsilon}_{i,t} &= \varepsilon_{i,t} + f_i(\varepsilon_{i,t}) - f_i(\varepsilon_{i,t-1}) - \beta_i f_i(\varepsilon_{i,t-1}) + \beta_i(\varepsilon_{i,t-2}) \\ &= \varepsilon_{i,t} + f_i(\varepsilon_{i,t}) - (1+\beta_i) f_i(\varepsilon_{it-1}) + \beta_i f_i(\varepsilon_{i,t-2})\end{aligned}$$

First lag autocovariance

$$\begin{aligned}cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) &= cov[\varepsilon_{i,t} + f_i(\varepsilon_{i,t}) - (1+\beta_i) f_i(\varepsilon_{i,t-1}) + \beta_i f_i(\varepsilon_{i,t-2}), \\ &\quad \varepsilon_{i,t-1} + f_i(\varepsilon_{i,t-1}) - (1+\beta_i) f_i(\varepsilon_{i,t-2}) + \beta_i f_i(\varepsilon_{i,t-3})] \\ &= cov\left[-(1+\beta_i) f_i(\varepsilon_{i,t-1}) + \beta_i f_i(\varepsilon_{i,t-2}), \varepsilon_{i,t-1} + f_i(\varepsilon_{i,t-1}) - (1+\beta_i) f_i(\varepsilon_{it-2})\right] \\ &= cov\left[-(1+\beta_i) f_i(\varepsilon_{i,t-1}), \varepsilon_{i,t} + f(\varepsilon_{i,t-1})\right] + cov\left[\beta_i f_i(\varepsilon_{i,t-2}), -(1+\beta_i) f_i(\varepsilon_{i,t-2})\right] \\ &= -(1+\beta_i)\left(cov\left[f_i(\varepsilon_{i,t-1}), \varepsilon_{i,t} + f(\varepsilon_{i,t-1})\right] + \beta_i var\left[f_i(\varepsilon_{i,t-2})\right]\right)\end{aligned}$$

Second lag autocovariance

$$\begin{aligned}cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-2}) &= cov[\varepsilon_{i,t} + f_i(\varepsilon_{i,t}) - (1+\beta_i) f_i(\varepsilon_{i,t-1}) + \beta_i f_i(\varepsilon_{i,t-2}), \\ &\quad \varepsilon_{i,t-2} + f_i(\varepsilon_{i,t-2}) - (1+\beta_i) f_i(\varepsilon_{i,t-3}) + \beta_i f_i(\varepsilon_{i,t-4})] \\ &= \beta_i cov\left[f_i(\varepsilon_{i,t-2}), \varepsilon_{i,t-2} + f_i(\varepsilon_{i,t-2})\right]\end{aligned}$$

Accruals measured with noise

The earnings are defined as $y_{i,t} = c_{i,t} + \Delta wc_{i,t}$, which can be rewritten in terms of observed earnings as

$$y_{i,t} = \tilde{y}_{i,t} + v_{i,t} - v_{i,t-1},$$

where $\tilde{y}_{i,t} = c_{i,t} + \Delta w\tilde{c}_{i,t}$ denotes the reported earnings. Note that in every period earnings contain the current accounting error, as well as the reversal of the error from the previous period. If we express the reported end-of-year balance of working capital in terms of the true accruals, $a_{i,t} = \Delta wc_{i,t}$, and the reported beginning-of-year working capital, we will also observe the error correction:

$$w\tilde{c}_{i,t} = \tilde{w}c_{i,t-1} + a_{i,t} + v_{i,t} - v_{i,t-1}.$$

If the true earnings follow AR(1) process, $y_{i,t} = \alpha_{i,t} + \beta_i y_{i,t-1} + \varepsilon_{i,t}$, then reported earnings can be expressed as

$$\begin{aligned}
\tilde{y}_{i,t} &= y_{i,t} + v_{i,t} - v_{i,t-1} \\
&= \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{i,t} + v_{i,t} - v_{i,t-1} \\
&= \alpha_i + \beta_i \left(\tilde{y}_{i,t-1} - v_{i,t-1} + v_{i,t-2}\right) + \varepsilon_{i,t} + v_{i,t} - v_{i,t-1} \\
&= \alpha_i + \beta_i \tilde{y}_{i,t-1} + \varepsilon_{i,t} + v_{i,t} - \left(1 + \beta_i\right) v_{i,t-1} + \beta_i v_{i,t-2.}
\end{aligned}$$

The structural error term $\tilde{\epsilon}_{i,t}$ therefore takes the form

$$\tilde{\epsilon}_{i,t} = \varepsilon_{i,t} + v_{i,t} - \left(1 + \beta_i\right) v_{i,t-1} + \beta_i v_{i,t-2.}$$

If we assume that $v_{i,t}$ is i.i.d. with variance σ_v^2, then the first and second lag autocovariances are as follows:

$$\begin{aligned}
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-1}) &= cov[\varepsilon_{i,t} + v_{i,t} - (1+\beta_i)\, v_{i,t-1} + \beta_i v_{i,t-2}, \varepsilon_{i,t-1} + v_{i,t-1} - (1+\beta_i)\, v_{i,t-2} + \beta_i v_{i,t-3}] \\
&= cov[-(1+\beta_i)\, v_{i,t-1} + \beta_i v_{i,t-2}, v_{i,t-1} - (1+\beta_i)\, v_{i,t-2}] \\
&= -(1+\beta_i)\sigma_v^2 - \beta_i(1+\beta_i)\sigma_v^2 \\
&= -(1+\beta_i)^2\sigma_v^2 \\
cov(\tilde{\epsilon}_{i,t}, \tilde{\epsilon}_{i,t-2}) &= cov[\varepsilon_{i,t} + v_{i,t} - (1+\beta_i)\, v_{i,t-1} + \beta_i v_{i,t-2}, \varepsilon_{i,t-2} + v_{i,t-2} - (1+\beta_i)\, v_{i,t-3} + \beta_i v_{i,t-4}] \\
&= cov[\beta_i v_{i,t-2}, v_{i,t-2}] \\
&= \beta_i \sigma_{v.}^2
\end{aligned}$$

Delayed recognition

Under delayed recognition, unbiased accounting earnings can be modeled using the following process

$$y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \theta_0 \varepsilon_{i,t} + \theta_1 \varepsilon_{i,t-1} + \theta_2 \varepsilon_{i,t-2}$$

in which $0 \leq \theta_j \leq 1$ for all j, $\theta_0 + \theta_1 + \theta_2 = 1$, $\beta_i > 0$, and $\varepsilon_{i,t}$ is an i.i.d. shock to the firm's performance. It is straightforward to extend this specification to k periods. This specification captures delayed recognition, because shocks to performance are eventually fully recognized into earnings, but recognition can take place over several periods.

For this specification, the autocovariances of the residuals from a regression of current earnings on lagged earning are non-negative for the first and second lags. Let $\epsilon_{i,t} = \theta_0 \varepsilon_{i,t} + \theta_1 \varepsilon_{i,t-1} + \theta_2 \varepsilon_{i,t-2}$. Then,

$$\begin{aligned}
cov(\epsilon_{i,t}, \epsilon_{i,t-2}) &= (\theta_0\theta_1 + \theta_1\theta_2)\sigma_\varepsilon^2 \\
cov(\epsilon_{i,t}, \epsilon_{i,t-2}) &= \theta_0\theta_2\sigma_\varepsilon^2,
\end{aligned}$$

both of which are always non-negative given that $0 \leq \theta_j \leq 1$.

In a similar manner one could model accounting conservatism, which in essence is a special form of conditional delayed recognition. Specifically, accounting conservatism requires that adverse shocks are recognized at their *present* value, taking into account all future effects of the adverse event, whereas positive shocks are recognized gradually over several periods. Formally, conservatism would take the form of $\theta_0 = 1$ and $\theta_1 = \theta_2 = 0$ if $\varepsilon_{i,t} < 0$, and $0 \leq \theta_j < 1$ for all j if $\varepsilon_{i,t} > 0$.

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Table 1: Derivation of sample: 1988–2008

This table presents the derivation of our sample. We pull all variables from the Compustat Fundamentals Annual File and require that firms report under SFAS 95. Our sample therefore starts in 1988 and ends in 2008.

Firm years with available cash flow from operations, lagged cash flow from operations, income before extraordinary items, lagged income before extraordinary items, total assets, lagged total assets, changes in accounts receivable, and changes in inventory	97,017
Firms years left after truncation of 1st and 99th percentiles of earnings before long term accruals, lagged earnings before long term accruals, earnings before extraordinary items, and lagged earnings before extraordinary items	89,481
Firms with 15 or more annual observations	1,664
Firm years for the 1,664 firms used in the analysis	29,185

Table 2: Descriptive statistics

This table presents descriptive statistics for the variables used in the analysis. We deflate all variables by lagged total assets (Compustat Item TA). $\tilde{c}_{i,t}$ is cash flow from operations (Compustat Item $OANCF$) minus cash flow related extraordinary items and discontinued operations (Compustat $XIDOC$). $\triangle\tilde{wc}_{i,t}$ is the change in working capital and is calculated using the cash flow statement method

$$\triangle\tilde{wc}_{i,t} = -1 * (RECCH + INVCH + APALCH + TXACH + AOLOCH)$$

in which $RECCH$ is the change in accounts receivable, $INVCH$ is the change in inventory, $APALCH$ is the change in accounts payable, $TXACH$ is the change in taxes payable, and $AOLOCH$ is the change in other assets and liabilities. We set missing values of $APALCH$, $TXACH$, and $AOLOCH$ are set equal to zero. $\tilde{e}_{i,t}$ is earnings before long term accruals and is calculated as $\tilde{c}_{i,t} + \triangle\tilde{wc}_{i,t}$. $\tilde{ib}_{i,t}$ is earnings before extraordinary items (Compustat Item IB). $ta_{i,t}$ is total assets in millions of US Dollars (Compustat Item TA).

	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
$\tilde{c}_{i,t}$	0.072	0.142	0.032	0.085	0.138
$\tilde{c}_{i,t-1}$	0.064	0.127	0.030	0.080	0.127
$\triangle\tilde{wc}_{i,t}$	0.015	0.087	-0.016	0.008	0.040
$\triangle\tilde{wc}_{i,t-1}$	0.010	0.076	-0.015	0.008	0.038
$\tilde{e}_{i,t}$	0.087	0.133	0.053	0.098	0.149
$\tilde{e}_{i,t-1}$	0.074	0.122	0.052	0.092	0.133
$\tilde{ib}_{i,t}$	0.020	0.150	0.004	0.044	0.087
$\tilde{ib}_{i,t-1}$	0.013	0.144	0.006	0.041	0.078
$ta_{i,t}$	3,891	19,117	56	331	1,796

Table 3: Coefficient estimates

This table presents coefficient estimates from the firm-level regressions of equations9 and 10:

$$\tilde{e}_{i,t} = \alpha_i + \beta_i \tilde{e}_{i,t-1} + \tilde{\epsilon}_{i,t}$$

$$\tilde{ib}_{i,t} = \alpha_i + \beta_i \tilde{ib}_{i,t-1} + \tilde{\epsilon}_{i,t}$$

We estimate these firm-level regressions using Stata's ARIMA function allowing the residuals to follow an AR(2) process

$$\tilde{\epsilon}_{i,t} = \rho_{i,1}\tilde{\epsilon}_{i,t-1} + \rho_{i,2}\tilde{\epsilon}_{i,t-2} + \varepsilon_{i,t}$$

in which $\varepsilon_{i,t}$ represents an idiosyncratic shock to the firm's performance. We use robust standard errors to address heteroscedasticity and classify a coefficient as statistically significant if its t statistic is greater than 1.95 in absolute value.

	$\tilde{e}_{i,t}$		$\tilde{ib}_{i,t}$	
	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\alpha}_i$	$\hat{\beta}_i$
Mean	0.0409	0.5327	0.0066	0.4256
Std. Dev.	0.0735	0.5520	0.0777	0.5460
25th Percentile	0.0077	0.1828	-0.0032	-0.0004
Median	0.0321	0.6410	0.0137	0.5169
75th Percentile	0.0727	0.9067	0.0357	0.8214

Table 4: AR(2) estimates

This table presents the distributions of AR(2) estimates for the firm-level regressions of equations 9 and 10. $\hat{\rho}_{i,1}$ ($\hat{\rho}_{i,2}$) is the estimate of the first lag (second lag) coefficient of the structural residuals. Estimates are classified as statistically significant if the coefficient's t statistic is greater than 1.95 in absolute value. These coefficients are estimated jointly with the coefficient estimates presented in Table 3.

	$\tilde{e}_{i,t}$		$\tilde{ib}_{i,t}$	
	$\hat{\rho}_{i,1}$	$\hat{\rho}_{i,2}$	$\hat{\rho}_{i,1}$	$\hat{\rho}_{i,2}$
Mean	0.107	-0.193	0.116	-0.212
Std. Dev.	0.499	0.295	0.524	0.308
25th Percentile	-0.249	-0.413	-0.262	-0.430
Median	0.065	-0.198	0.070	-0.229
75th Percentile	0.428	0.016	0.466	-0.005
Significantly Positive (%)	20	2	21	3
Significantly Negative (%)	11	22	13	25

Table 5: Economic shocks and macroeconomic factors

This table presents pooled ordinary least squares regressions that estimate associations between our measure of firm level economic shocks and four macroeconomic factors: the annual percentage change in GDP; inflation; and the annual change in the one year US Treasury rate. The dependent variable for the regressions is the residual, $\varepsilon_{i,t}$, from the estimation of equations 9 and 10. Standard errors are in parentheses and are clustered at the annual level.

Panel A: Earnings before long term accruals

	I	II	III	IV
Change in GDP	0.0039***			0.0035***
	(0.0007)			(0.0007)
Inflation		-0.0186**		-0.0133**
		(0.0074)		(0.0053)
Change in 1 year Treasury			0.0021***	0.0001
			(0.0006)	(0.0006)
Constant	-0.0202***	0.0191**	0.0007	-0.0046
	(0.0039)	(0.0075)	(0.0009)	(0.0064)
Adj. R^2	0.0042	0.0010	0.0029	0.0046
p Value	0.0000	0.0230	0.0027	0.0000
Observations	25,106	25,106	25,106	25,106

* p<.1, ** p<.05, *** p<.01, two-sided test

Panel B: Earnings before extraordinary items

	I	III	III	IV
Change in GDP	0.0061***			0.0049***
	(0.0015)			(0.0016)
Inflation		-0.0244		-0.0158
		(0.0231)		(0.0149)
Change in 1 year Treasury			0.0035***	0.0008
			(0.0012)	(0.0011)
Constant	-0.0317***	0.0248	0.0007	-0.0093
	(0.0089)	(0.0223)	(0.0014)	(0.0150)
Adj. R^2	0.0063	0.0011	0.0048	0.0067
p Value	0.0009	0.3054	0.0086	0.0010
Observations	24,819	24,819	24,819	24,819

* p<.1, ** p<.05, *** p<.01, two-sided test

Table 6: Smoothed portion of earnings and macroeconomic factors

This table presents ordinary least squares regressions that estimate associations between the smoothed portions of earnings before long term accruals and earnings before extraordinary items and four macroeconomic factors: the annual percentage change in GDP; inflation; and the annual change in the one year US Treasury rate. The dependent variables are the autocorrelated components of the structural error terms, $\rho_{i,1}\epsilon_{i,t-1} + \rho_{i,2}\epsilon_{i,t-2}$, from the estimation of equations 9 and 10. Standard errors are in parentheses and are clustered at the annual level.

Panel A: Earnings before long term accruals

	I	II	III	IV
Change in GDP	0.0003			0.0011*
	(0.0004)			(0.0004)
Inflation		-0.0061*		-0.0061*
		(0.0034)		(0.0033)
Change in 1 year Treasury			-0.0001	-0.0007*
			(0.0002)	(0.0004)
Constant	-0.0012	0.0067*	0.0004	0.0006
	(0.0020)	(0.0034)	(0.0004)	(0.0044)
Adj. R^2	0.0001	0.000	0.0002	0.0004
p Value	0.4052	0.7131	0.0880	0.0005
Observations	25,106	25,106	25,106	25,106

* p<.1, ** p<.05, *** p<.01, two-sided test

Panel B: Earnings before extraordinary items

	I	II	III	IV
Change in GDP	0.0012**			0.0025***
	(0.0004)			(0.0007)
Inflation		0.0019		0.0033
		(0.0046)		(0.0044)
Change in 1 year Treasury			0.0003	-0.0010*
			(0.0002)	(0.0005)
Constant	-0.0058**	-0.0012	0.0009	-0.0157***
	(0.0024)	(0.0049)	(0.0006)	(0.0051)
Adj. R^2	0.0006	0.0000	0.0001	0.0009
p Value	0.0108	0.6840	0.1929	0.0051
Observations	24,819	24,819	24,819	24,819

* p<.1, ** p<.05, *** p<.01, two-sided test

Table 7: Accruals quality and earnings smoothing measures

This table describes accruals quality and earnings smoothing measures used in prior research. All four measures are estimated on a firm-level basis for the 1,664 firms in the sample. $Correlation_i$ is the contemporaneous Spearman correlation between the change in cash flow from operations and the change in working capital accounts. $Ratio_i$ is the standard deviation of operating income divided by the standard deviation of cash flow from operations. $Jones_i$ is 1 minus the R^2 from a firm-level modified Jones model. $DechowDichev_i$, is negative one times the standard deviation of the residuals from a firm-level regression of the change in working capital on lagged, current, and future cash flow from operations. Panel A presents the deceptive statistics for the measures and Panel B presents their Pearson correlations.

Panel A: Descriptive statistics

	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
$Correlation_i$	-0.653	0.245	-0.841	-0.711	-0.503
$Ratio_i$	1.023	0.531	0.682	0.934	1.252
$Jones_i$	0.756	0.197	0.641	0.804	0.915
$DechowDichev_i$	-0.033	0.026	-0.042	-0.025	-0.015

Panel B: Correlation Matrix

	$Correlation_i$	$Ratio_i$	$Jones_i$
$Ratio_i$	0.388		
$Jones_i$	-0.022	-0.021	
$DechowDichev_i$	-0.207	-0.249	0.046

Table 8: Accruals quality and earnings smoothing measures by $\hat{\rho}_{i,2}$ deciles

This table presents means of the earnings management measures tabulated by the decile of the firm-level second lag coefficient estimates, $\hat{\rho}_{i,2}$, for earnings before long term accruals and earnings before extraordinary items. Definitions of the accruals quality and earnings smoothing measures are provided in Table 7.

Panel A: Earning before long term accruals

Decile	$\hat{\rho}_{i,2}$	$Correlation_i$	$Ratio_i$	$Jones_i$	$DechowDichev_i$
10	0.331	-0.673	1.072	0.732	-0.030
9	0.134	-0.661	0.993	0.778	-0.034
8	0.014	-0.664	1.084	0.753	-0.031
7	-0.073	-0.673	1.045	0.754	-0.034
6	-0.159	-0.672	0.941	0.738	-0.030
5	-0.240	-0.645	1.109	0.778	-0.040
4	-0.324	-0.634	0.966	0.767	-0.032
3	-0.415	-0.668	0.980	0.762	-0.031
2	-0.516	-0.615	0.989	0.737	-0.036
1	-0.674	-0.624	1.044	0.767	-0.034

Panel B: Earnings before extraordinary items

Decile	$\hat{\rho}_{i,2}$	$Correlation_i$	$Ratio_i$	$Jones_i$	$DechowDichev_i$
10	0.353	-0.683	0.922	0.763	-0.030
9	0.126	-0.640	1.060	0.765	-0.036
8	-0.005	-0.663	1.037	0.742	-0.031
7	-0.100	-0.658	1.001	0.744	-0.037
6	-0.187	-0.688	0.933	0.789	-0.032
5	-0.269	-0.654	1.021	0.777	-0.033
4	-0.348	-0.604	1.098	0.752	-0.031
3	-0.433	-0.660	0.989	0.762	-0.034
2	-0.539	-0.630	1.072	0.756	-0.034
1	-0.717	-0.643	1.027	0.745	-0.035

Table 9: Accruals quality and earnings smoothing measures by $\hat{\sigma_i}(\varepsilon_{i,t})$ deciles

This table presents means of the second lag coefficient estimates and the earnings management measures tabulated by the decile of the firm-level estimates of the volatility of economic shocks, $\hat{\sigma_i}(\varepsilon_{i,t})$, for earnings before long term accruals and earnings before extraordinary items. Definitions of the accruals quality and earnings smoothing measures are provided in Table 7.

Panel A: Earning before long term accruals

Decile	$\hat{\sigma_i}(\varepsilon_{i,t})$	$\hat{\rho}_{i,2}$	$Correlation_i$	$Ratio_i$	$Jones_i$	$DechowDichev_i$
10	0.159	-0.193	-0.395	1.255	0.755	-0.080
9	0.089	-0.207	-0.551	1.176	0.754	-0.057
8	0.067	-0.212	-0.582	1.192	0.758	-0.042
7	0.053	-0.165	-0.628	1.120	0.758	-0.036
6	0.042	-0.231	-0.671	1.044	0.739	-0.030
5	0.035	-0.179	-0.681	1.021	0.756	-0.025
4	0.028	-0.197	-0.724	0.969	0.766	-0.021
3	0.023	-0.216	-0.745	0.912	0.754	-0.018
2	0.017	-0.117	-0.756	0.796	0.753	-0.014
1	0.011	-0.211	-0.795	0.741	0.772	-0.010

Panel B: Earnings before extraordinary items

Decile	$\hat{\sigma_i}(\varepsilon_{i,t})$	$\hat{\rho}_{i,2}$	$Correlation_i$	$Ratio_i$	$Jones_i$	$DechowDichev_i$
10	0.205	-0.166	-0.446	1.484	0.766	-0.073
9	0.119	-0.224	-0.518	1.370	0.758	-0.058
8	0.084	-0.226	-0.571	1.298	0.748	-0.043
7	0.065	-0.211	-0.653	1.134	0.762	-0.036
6	0.051	-0.254	-0.694	1.011	0.765	-0.029
5	0.040	-0.224	-0.658	0.930	0.779	-0.025
4	0.031	-0.199	-0.738	0.867	0.768	-0.023
3	0.024	-0.190	-0.744	0.843	0.756	-0.018
2	0.016	-0.212	-0.748	0.691	0.757	-0.015
1	0.008	-0.215	-0.750	0.536	0.734	-0.011