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Earnings Volatility and Earnings Prediction: Analysis and UK Evidence

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Abstract: This paper confirms that US evidence of a negative relationship between earnings persistence and earnings volatility applies to UK firms over the period 1991–2010. Our analytical framework highlights the possibility that this result may reflect downward estimation bias in earnings persistence (and persistence of cash flow and accruals components of earnings) related to transitory earnings elements. Out-of-sample forecasts, based on models estimated for earnings volatility quartiles, suggest significant improvement in earnings forecasts for lower volatility firms. The results also suggest that the negative association between earnings persistence and volatility may be due to both estimation bias and variation in core earnings persistence.

Keywords: earnings volatility, persistence, core and transitory earnings, earnings prediction and forecasting

1. INTRODUCTION

The role of earnings volatility in earnings prediction has been highlighted as an important issue for financial accounting research in an empirical study by Dichev and Tang (2009). Their study provides strong evidence based on US data that earnings persistence is negatively related to earnings volatility. They argue their findings are consistent with previous survey evidence by Graham et al. (2005) on executives' beliefs that earnings predictability is negatively related to earnings volatility and suggest that future research might "expand and solidify these results using other samples and variable definitions" (p. 180).

In the light of the previous analysis by Dichev and Tang (2009), the current paper aims to contribute to the literature in two main respects. First, we develop a simple framework for analysis of the relationship between earnings volatility and earnings persistence which highlights the possible role of transitory earnings in this

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relationship. This framework, building on previous analysis by Richardson et al. (2005), suggests that a negative relationship between earnings volatility and earnings persistence may be related to downward estimation bias in earnings persistence and outlines the implications of this possibility for earnings forecasting. Second, we use our analytical framework as the basis for an empirical analysis of the impact of earnings volatility on prediction model estimation and earnings forecasting. In particular, our empirical analysis, based on UK data for the period 1991–2010, provides evidence on the usefulness of volatility-related variation in estimated earnings persistence for the accuracy of earnings forecasts.

The remainder of the paper is organized as follows. Section 2 reviews previous empirical research on earnings volatility and earnings persistence, in particular the studies of Dichev and Tang (2009) and Frankel and Litov (2009), and summarizes key findings and issues raised by these papers. Section 3 presents our framework for understanding the negative relationship between earnings persistence and earnings volatility centred on an 'errors-in-variable' (EIV hereafter) perspective. Section 4 outlines our empirical research design and reports empirical results on the impact of earnings volatility on prediction model estimation and earnings forecasting. Section 5 summarizes and concludes the paper.

2. PREVIOUS EMPIRICAL RESEARCH ON EARNINGS VOLATILITY AND EARNINGS PERSISTENCE

Dichev and Tang (2009) provide compelling evidence that earnings persistence is negatively associated with earnings volatility for US firms over the period 1988–2008. They motivate their analysis with reference to previous survey evidence by Graham et al. (2005) that managers widely believe that earnings volatility is associated with reduced earnings predictability, where the notion of earnings predictability is assumed to correspond closely to the concept of earnings persistence. While they note that economic and/or accounting factors might drive the negative association between earnings volatility and persistence, they emphasize that their analysis focuses on empirical evidence of the extent and importance of the relationship rather than its cause.[1]

The empirical analysis of Dichev and Tang (2009) is based on estimation of an autoregressive earnings prediction model for a large sample of US firm-year observations partitioned into earnings volatility quintiles. They show that estimated earnings persistence falls from 0.934 to 0.507 between low and high volatility quintiles, where the latter is defined in terms of standard deviation of earnings estimated over a 5 year period. These results are supported by further analysis showing median future earnings for low and high volatility quintiles which indicate almost constant median annual profitability over a future period of 5 years for low volatility firms, in contrast to significant mean reversion and generally less stable future earnings for the high earnings volatility quintile. In robustness tests, they show that eliminating firms with high special items does not alter the tenor of their regression results, arguing that:

1 In relation to economic factors, they argue that "intuitively, firms operating in environments subject to large economic shocks are likely to have both more volatile earnings and less predictable earnings" (p. 161). In relation to accounting factors, they point out that previous research by Dichev and Tang (2008) shows how the mismatching of revenues and expenses in the accruals process can lead to transitory noise in earnings.

> "the documented strong relation between earnings volatility and earnings predictability is rooted in the full sample and is not limited to the effect of transitory items or the rising frequency of special items over time" (p. 172).

They also provide evidence showing how earnings volatility quintiles are monotonically related to proxies for economic factors such as cash flow volatility and to proxies for accounting measurement effects such as accruals volatility. Consistent with the broader research literature on earnings quality reviewed by Dechow et al. (2010), their analysis suggests that both economic and accounting factors are likely to be playing a role in the relationship between earnings volatility and persistence.

In a discussion of the Dichev and Tang (2009) study, Frankel and Livov (2009) point out that the negative volatility/persistence relationship does indeed require explanation because, *ceteris paribus*, a positive statistical relationship between volatility and persistence might be expected (see section 3 below for further discussion of this point). In addition to confirming that the negative earnings volatility/persistence relationship is robust to inclusion of additional firm characteristics, they further consider the relative importance of economic and accounting factors as drivers of this relationship by comparing the effect of volatility on univariate earnings and cash flow prediction models. In particular, they argue that if accounting factors drive this relationship, there should be a weaker relationship between cash flow volatility and cash flow persistence than between earnings volatility and earnings persistence. Their empirical findings, however, indicate a marginally stronger negative association for cash flow, leading them to argue that:

> "... if we assume that earnings and cash-flow capture similar economic phenomena ... these results suggest that accruals errors are not a significant driver of the relation between variance and persistence"(p.186).

The analyses of Dichev and Tang (2009) and Frankel and Litov (2009) raise important issues considered in the current study. In particular:

- The finding of Dichev and Tang that the negative relationship is not explained by special items raises the possibility that transitory elements within earnings measured *before* special items may be driving this relationship. If transitory elements in earnings are driving this relationship, our framework (see section 3) shows that the negative relationship will be based on volatility-induced downward estimation bias in earnings persistence and that this will have potentially significant implications for earnings forecasting.
- The finding of Frankel and Litov that cash flow volatility drives estimates of cash flow persistence highlights the potential differential effects of volatility on cash flow and accruals persistence and the possible implications of such differential effects for earnings forecasting. Building on this perspective, we consider (i) the impact of volatility on the estimated persistence of both cash flow and accruals components of earnings, and (ii) its impact on earnings forecasts based on multivariate prediction models which use cash flow and accruals components of earnings as predictor variables.

In summary, our framework and empirical analysis aims (i) to provide UK evidence on the relationship between earnings volatility and earnings persistence, and (ii) to address important questions arising from previous US research concerning the nature of this relationship and the implications for earnings forecasting.

3. A FRAMEWORK FOR ANALYZING THE EARNINGS PERSISTENCE/VOLATILITY RELATIONSHIP

We start by assuming that firms can be grouped according to the persistence of their earnings and that all components of a firm's earnings have the same persistence. In this setting, we argue that earnings correspond exactly to "core earnings" as there are no transitory (or lower persistence) earnings components.[2] Furthermore, if core earnings for any firm in group i at date t+1, E^*_{it+1}, is assumed to be given by:[3]

$$E^*_{it+1} = \gamma_i E^*_{it} + \varepsilon_{it+1} \tag{1}$$

where persistence of core earnings for group i firms,γ_i, satisfies $0 < \gamma_i < 1$ and ε_{it+1} is an independently distributed mean zero disturbance term with constant variance $\sigma^2_{\varepsilon_i}$, it follows that the variance of core earnings for group i firms is:

$$\sigma^2_{E^*_i} = \sigma^2_{\varepsilon_i} / \left(1 - \gamma_i^2\right). \tag{2}$$

If we assume that disturbance term volatility in equation (1) is constant for all firm groups such that $\sigma^2_{\varepsilon_i} = \sigma^2_{\varepsilon}$ $i = 1, 2, \ldots n$ (where n is the number of groups based on core earnings persistence), it follows from equation (2) that core earnings volatility, $\sigma^2_{E^*_i}$, is positively related to γ_i. Alternatively, if $\sigma^2_{\varepsilon_i}$ is not constant across groups but is distributed independently of γ_i, a positive association between $\sigma^2_{E^*_i}$ and γ_i is also implied. In other words, consistent with the analysis of Frankel and Litov (2009), a positive (rather than a negative) "mechanical" relationship between earnings persistence and volatility is implied in this setting. In the absence of low persistence or transitory items in earnings, we conclude that a negative relationship between earnings persistence and earnings volatility requires a sufficiently strong negative relationship between persistence γ_i and disturbance term volatility $\sigma^2_{\varepsilon_i}$ across firm groups $i = 1, 2, \ldots n$ to overcome the effect of the positive impact of earnings persistence on earnings volatility implied by equation (2).

While the negative empirical relationship between earnings persistence and earnings volatility quintiles reported by Dichev and Tang (2009) may be related to a negative correlation between core earnings persistence and disturbance term volatility as considered above, an alternative statistical explanation, consistent with previous analysis by Richardson et al. (2005), is that it may be due to the presence of transitory elements in reported earnings. To show this, we now define reported earnings as the sum of core earnings and transitory earnings such that for any firm in group i, with core persistence γ_i, reported earnings can be written as:

$$E_{it} = E^*_{it} + u_{it}, \tag{3}$$

2 Our use of the term "core earnings" is in the spirit of modern financial statement analysis and valuation texts, such as Penman (2013), which uses the term to refer to the part of current earnings useful for predicting future earnings.

3 We assume that earnings are expressed as the deviation from the population mean, so that it is not necessary to include an intercept term in equation (1). This is convenient for presentational purposes and consistent with prior research such as Richardson et al. (2005).

where u_{it} is an independent mean-zero transitory earnings term with constant variance $\sigma^2_{u_i}$ and where the variance of reported earnings for any firm in group i is therefore given by:

$$\sigma^2_{E_i} = \sigma^2_{E^*_i} + \sigma^2_{u_i}. \tag{4}$$

Using equation (4) in equation (1) implies the following prediction model for reported earnings:

$$E_{it+1} = \gamma_i E_{it} + (\varepsilon_{it+1} + u_{it+1} - \gamma_i u_{it}), \tag{5}$$

where $(\varepsilon_{it+1} + u_{it+1} - \gamma_i u_{it})$ is a mean-zero disturbance term. Given that E_{it} and the disturbance term in equation (5) are correlated due to the presence of u_{it} in both, application of standard EIV analysis implies the following downwardly biased estimator for core earnings persistence (Maddala, 1989):

$$\hat{\gamma}_i = \gamma_i \sigma^2_{E^*_i} / \left(\sigma^2_{E^*_i} + \sigma^2_{u_i}\right). \tag{6}$$

Equation (6) highlights the reduction in estimated earnings persistence caused by higher levels of $\sigma^2_{u_i}$. In other words, earnings volatility arising from transitory earnings has a negative effect on estimated earnings persistence, possibly leading to the negative relationship between estimated persistence and earnings volatility highlighted by Dichev and Tang (2009) and Frankel and Litov (2009).

In summary, our simple analysis in equations (1)–(6) indicates that if firms are partitioned into n groups, where γ_i, $\sigma^2_{\varepsilon_i}$, and $\sigma^2_{u_i}$ are the relevant parameters for any group i, then a negative relationship between earnings volatility and estimated earnings persistence must be due to one or both of the following:

- a negative relationship between γ_i and $\sigma^2_{\varepsilon_i}$ across firm groups $i = 1, 2, \ldots n$; and
- the impact of variation in $\sigma^2_{u_i}$ on estimated persistence $\hat{\gamma}_i$ across firm groups $i = 1, 2, \ldots n$.

While the previous univariate analysis provides possible statistical explanations for the empirical results in Dichev and Tang (2009), different components of earnings may (i) have different persistence and/or (ii) be affected by transitory elements to different degrees (leading to differences in the extent of downward estimation bias in their persistence coefficients). In particular, a model where earnings are divided into cash flow from operations and accruals components allows us to build on previous multivariate EIV analysis by Richardson et al. (2005) which assumed that transitory earnings were related solely to accrual measurement errors.[4] Our EIV perspective raises the possibility that reductions in estimated cash flow persistence related to cash flow volatility may be due to the effect of transitory cash flow elements caused by real economic events.

4 Substantial previous research has considered the differential role of cash flow and accruals components in earnings prediction and/or equity valuation. See, for example, Sloan (1996), Barth et al. (1999), and Konstantinidi and Pope (2012). There is also a significant literature on the related issue of cash flow prediction which emphasizes the roles of cash flow and accruals components of earnings, for example Barth et al. (2001) and Al-Atar and Hussain (2004).

Our empirical analysis therefore focuses on a multivariate model where earnings are divided into cash flow from operations and accruals, with the latter further divided into working capital accruals, depreciation and amortization, and other accruals. The multivariate equivalent of equations (1) and (5) for a particular firm group *i* are given by:

$$E^*_{it+1} = \gamma_{Ci} C^*_{it} + \gamma_{Wi} W^*_{it} + \gamma_{Di} D^*_{it} + \gamma_{Oi} O^*_{it} + \varepsilon_{it+1} \tag{7}$$

and:

$$E_{it+1} = \gamma_{Ci} C_{it} + \gamma_{Wi} W_{it} + \gamma_{Di} D_{it} + \gamma_{Oi} O_{it} + \omega_{it+1} \tag{8}$$

where:

C^*_{it}, W^*_{it}, D^*_{it} and O^*_{it} represent core measures of cash flow from operations, working capital accruals, depreciation and amortization, and other accruals, respectively, at date t with persistence of γ_{Ci}, γ_{Wi}, γ_{Di} and γ_{Oi}, respectively (and where $E^*_{it} \equiv C^*_{it} + W^*_{it} + D^*_{it} + O^*_{it}$); $C_{it} = C^*_{it} + u_{Cit}$, $W_{it} = W^*_{it} + u_{Wit}$, $D_{it} = D^*_{it} + u_{Dit}$ and $O_{it} = O^*_{it} + u_{Oit}$ represent the reported earnings components and u_{Cit}, u_{Wit}, u_{Dit} and u_{Oit} represent mean zero transitory elements of the four earnings components at date t (and hence $u_{Eit} = u_{Cit} + u_{Wit} + u_{Dit} + u_{Oit}$); and $\omega_{it+1} = (\varepsilon_{it+1} + u_{Eit+1} - \gamma_{Ci} u_{Cit} - \gamma_W u_{Wit} - \gamma_{Di} u_{Dit} - \gamma_O u_{Oit})$ is a mean zero disturbance term at date *t+1*.

Equations (7) and (8) extend equations (1) and (5) by permitting: (i) differences between the core persistence of earnings components *i*, γ_{Ci}, γ_{Wi}, γ_{Di} and γ_{Oi} for a given group, and (ii) further possible differences between coefficient estimates $\hat{\gamma}_{Ci}$, $\hat{\gamma}_{Wi}$, $\hat{\gamma}_{Di}$ and $\hat{\gamma}_{Oi}$ related to the variance of the transitory elements of each of the components $\sigma^2_{u_{Ci}}$, $\sigma^2_{u_{Wi}}$, $\sigma^2_{u_{Di}}$ and $\sigma^2_{u_{Oi}}$. In a similar vein to the univariate case, a negative relationship between one or more earnings component persistence coefficients and core earnings disturbance term volatility, $\sigma^2_{\varepsilon_i}$, could provide a possible explanation for multivariate results showing a negative relationship between earnings component persistence and earnings volatility. Alternatively, similar to the univariate case shown in equation (6), standard EIV analysis based on equation (8) suggests that the magnitude of the variance of the transitory elements associated with each earnings component will contribute to downward bias in the corresponding component persistence estimate.[5]

While our initial empirical analysis in section 4 provides results on the impact of volatility on the estimation of earnings prediction models, these results do not provide direct evidence for distinguishing between "core persistence" and "biased persistence" explanations of a negative volatility–persistence relationship. A focus on the accuracy of out-of-sample earnings forecasts based on the two perspectives,

5 It should be noted that EIV analysis for the multivariate case is more complex than for the univariate case. First, any covariance between transitory elements of the different earnings components may cause complex interactions in biases in the various component coefficient estimates. Second, assuming independence between transitory elements of different components, the correlation structure of the earnings components affects how transitory elements in one component affects bias in the estimation of the coefficient for other variables (Maddala, 1989). In summary, the variance of transitory elements in a particular variable will generate downward bias in the coefficient for that variable under strong assumptions of independence. However, the more realistic assumption of correlation between earnings components (and their transitory elements) creates additional complexities in terms of the impact of transitory elements in one component on estimation bias in the coefficient of another component.

however, should provide useful evidence on these competing explanations. More specifically, a "core persistence" perspective implies that forecasts of earnings at date $t+1$ based on estimated persistence coefficients and current earnings components at date t for a particular group i will be optimal. On the other hand, if transitory earnings elements are present and the "biased persistence" perspective is correct, it is clear from rearranging equation (8) making use of the definition of ω_{it+1} that future earnings for firms in group i will be generated by:

$$E_{it+1} = \gamma_{Ci} C^*_{it} + \gamma_{Wi} W^*_{it} + \gamma_{Di} D^*_{it} + \gamma_{Oi} O^*_{it} + (\varepsilon_{it+1} + u_{Eit+1}). \tag{9}$$

Equation (9) indicates that earnings forecasts should ideally be based on (i) core persistence, and (ii) current core (rather than reported) earnings components. In other words, if the "biased persistence" perspective is correct, this implies the need for adjustments to both estimated persistence coefficients and reported earnings. The different implications of our two explanations of the negative persistence/volatility relationship for earnings forecasting provide the basis for alternative approaches to earnings forecasting described in section 4 of the paper.

4. EMPIRICAL RESEARCH DESIGN AND RESULTS

(i) Empirical Models and Tests

Our empirical analysis is based on estimation of the following univariate and multivariate regression models for sample firms partitioned into volatility quartiles:

$$\text{Model 1}: E_{qt+1} = a_{1q} + a_{Eq} E_{qt} + \varepsilon_{1qt+1},$$

$$\text{Model 2}: E_{qt+1} = a_{2q} + a_{Cq} C_{qt} + a_{Wq} W_{qt} + a_{Dq} D_{qt} + a_{Oq} O_{qt} + \varepsilon_{2qt+1},$$

where E_{qt}, C_{qt}, W_{qt}, D_{qt} and O_{qt} are earnings, cash flow from operations, working capital accruals, depreciation and other accruals, respectively (all scaled by average total assets) at date t for a firm in volatility quartile q (where $q = 1$ denotes the quartile of firms with lowest volatility and $q = 4$ denotes the quartile of firms with highest volatility), a_{Eq}, a_{Cq}, a_{Wq}, a_{Dq} and a_{Oq} are estimated coefficients for regressions based on quartile q firms, a_{1q} and a_{2q} are estimated model 1 and 2 intercepts for regressions based on quartile q firms, and ε_{1qt+1} and ε_{2qt+1} are mean zero error terms in these regressions.

Model 1 is estimated for firm quartiles based on earnings volatility, while model 2 is estimated not only for earnings volatility quartiles but also for cash flow and working capital accruals volatility quartiles. The firm volatility measures are as follows:

- Earnings volatility is the standard deviation of earnings scaled by average total assets.
- Cash flow volatility is the standard deviation of cash flow from operations scaled by average total assets.

- Working capital accruals volatility is the standard deviation of working capital accruals scaled by average total assets.

Based on the US findings discussed previously, we expect $a_{E1} > a_{E2} > a_{E3} > a_{E4}$ for model 1 regressions based on earnings volatility quartiles. Similarly, for model 2 regressions based on earnings volatility quartiles, we would expect $a_{C1} > a_{C2} > a_{C3} > a_{C4}$, $a_{W1} > a_{W2} > a_{W3} > a_{W4}$, $a_{D1} > a_{D2} > a_{D3} > a_{D4}$ and $a_{O1} > a_{O2} > a_{O3} > a_{O4}$ *either* if the core persistence of each of these coefficients is negatively related to the volatility of the disturbance term in equation (7) *or* if volatility of transitory elements in each of our four earnings component is positively related to overall earnings volatility. Differences across components in the strength (if any) of the association between estimated persistence and earnings volatility might, however, also be expected (for example, due to the differences in the significance of transitory elements in different earnings components). Finally, for model 2 regressions based on cash flow from operations volatility quartiles and working capital accruals volatility quartiles, we would expect $a_{C1} > a_{C2} > a_{C3} > a_{C4}$ and $a_{W1} > a_{W2} > a_{W3} > a_{W4}$, respectively *either* if these volatility measures proxy for the extent of transitory elements in cash flow and working capital accruals *or* if lower core persistence for each of these components is associated with their own volatility (as well as earnings volatility more generally).[6]

Following analysis of the impact of volatility on estimation of earnings prediction models for our complete sample period 1991–2010 (which generate results broadly consistent with previous US findings reviewed in section 2), we focus on using estimates of model 2 to forecast future earnings. We forecast earnings recursively for each year during the period 2001–10 using regression models based on the previous 10 years of data up to the forecast year. The following three forecasting approaches are used:

QS forecast model – "Quartile specific forecast model", so that for a firm in earnings volatility quartile q, the forecast is given by:

$$Forecast\left[E_{qt+1}\right] = a_{2q} + a_{Cq}C_{qt} + a_{Wq}W_{qt} + a_{Dq}D_{qt} + a_{Oq}O_{qt},$$

i.e. persistence estimates for each firm's own specific quartile are used.

Q1 forecast model – "Quartile 1 forecast model" is used for *all* firms, so that for a firm in earnings volatility quartile q, the forecast is given by:

$$Forecast\left[E_{qt+1}\right] = a_{21} + a_{C1}C_{qt} + a_{W1}W_{qt} + a_{D1}D_{qt} + a_{O1}O_{qt},$$

i.e. persistence estimates from the lowest volatility quartile are used for all firms.

FS forecast model – "Full sample forecast model" is used for *all* firms, so that for a firm in earnings volatility quartile q, the forecast is given by:

$$Forecast\left[E_{qt+1}\right] = a_{2} + a_{C}C_{qt} + a_{W}W_{qt} + a_{D}D_{qt} + a_{O}O_{qt},$$

i.e. persistence estimates from the full sample of firms are used for all firms.

6 The possible effects of cash flow and working capital accrual volatility partitions on the coefficients of the other earnings components in model 2 regressions are not immediately obvious but are briefly considered in the discussion of our empirical results.

In order to explain our use of these three forecast models, we briefly consider two extreme scenarios using notation from section 3. Scenario 1 corresponds to the case where a negative relationship between earnings volatility and persistence is solely due to differences in core persistence. Scenario 2 corresponds to the case where such a relationship is solely due to estimation bias.

> *Scenario 1* – There are no transitory elements in any of the four earnings components such that $u_{Eqt} = u_{Cqt} = u_{Wqt} = u_{Dqt} = u_{Oqt} = 0, \forall q, t$ and there are differences in core earnings component persistence coefficients between volatility quartiles.
> *Scenario 2* – There are no transitory earnings for quartile 1 firms, so that $u_{E1t} = u_{C1t} = u_{W1t} = u_{D1t} = u_{O1t} = 0, \forall t$. There are transitory earnings for firms in quartiles 2, 3 and 4 such that $\sigma^2_{u_{E2}}$, $\sigma^2_{u_{E3}}$ and $\sigma^2_{u_{E4}}$ are all positive (and hence for q = 2, 3, 4 *at least* one of $\sigma^2_{u_{Cq}}$, $\sigma^2_{u_{Wq}}$, $\sigma^2_{u_{Dq}}$ and $\sigma^2_{u_{Oq}}$ is positive). All firms have the same core earnings component persistence (i.e. in terms of terminology in section 3, core earnings component persistence denoted γ_C, γ_W, γ_D and γ_O are the same for *all* firms).

Under scenario 1, differences in persistence coefficients across different volatility quartiles represent differences in core persistence and hence the QS forecast model is optimal. Under this scenario, forecasts based on the FS model may be superior on average to forecasts based on the Q1 forecast model.

Under scenario 2, the Q1 forecast model has the advantage of using unbiased estimates i.e. the expected values of a_{C1}, a_{W1}, a_{D1} and a_{O1} are γ_C, γ_W, γ_D and γ_O, respectively. However, a limitation of forecasts from this model under this scenario is that even if a_{C1}, a_{W1}, a_{D1} and a_{O1} are equal to γ_C, γ_W, γ_D and γ_O, respectively, forecast errors will arise due to the presence of transitory elements in C_{qt}, W_{qt}, D_{qt} and O_{qt} for $q = 2, 3, 4$ (as shown by equation (9), a forecast of date $t + 1$ earnings under scenario 2 should ideally be based not only on core earnings component persistence but also on measures of core, not reported, earnings components at date t). Hence, while we would expect Q1 model forecasts to be superior for some firms under scenario 2, it is also likely that QS and/or FS model forecasts will be superior to Q1 forecasts for some firms.

In our empirical analysis, we use mean and median absolute forecast errors across our 10 year forecast period to measure the accuracy of these models. We interpret greater accuracy of the QS forecast model as consistent with earnings volatility being related to lower core persistence. We interpret greater accuracy of the Q1 model, on the other hand, as consistent with earnings volatility being related to downward bias in persistence estimates. More mixed results where it is difficult to distinguish between the three models would probably suggest *both* lower core persistence and downward estimation bias effects.[7]

7 Note that the FS forecast model might perform favourably in some cases. For example, for high volatility firms in quartiles 3 or 4, estimated persistence coefficients for the whole sample (used in the FS forecast model) may provide superior estimates of core persistence than estimates based on quartile 1 firms (used in the Q1 model) or estimates from their own quartile (used in the QS model) when both effects are present. For these firms, coefficients used in Q1model forecasts may be too high due to lower core persistence of these high volatility firms and coefficients used in QS model forecasts may be too low due to the effect of downward estimation bias.

(ii) Data and Descriptive Statistics

The data for the empirical analysis are extracted from WorldScope and are based on all non-financial companies listed in the London Stock Exchange between 1991 and 2010. The following variables scaled by average total assets are used in the empirical analysis: earnings (E) are after-tax income from continuing operations; cash flow (C) is cash flow from operations after interest and tax paid; working capital accruals (W) are based on changes in accounts receivable, inventory and accounts payable from the cash flow statement; depreciation (D) is the depreciation and depletion expense multiplied by -1; and other accruals (O) are the total of other accrual items estimated as $E-(C+W+D)$. After excluding financial companies, the initial sample consists of 18,366 firm-year observations based on 2,881 firms. After eliminating firm-years with some missing data and those corresponding to the most extreme 1% of E, C and W, the sample reduces to 17,344 firm-year observations based on 2,545 firms. Finally, after elimination of those cases without the 3 years of data required to estimate earnings volatility (and 2 years of consecutive data required for use in the prediction model estimation), the final sample amounts to 16,847 firm-year observations based on 2,301 firms.

Panel A of Table 1 provides descriptive statistics for the variables used in our empirical analysis. Cash flow (C), earnings (E) and working capital accruals (W) have positive means and medians as expected, while other accruals (O) has a negative mean and median consistent with such accruals reflecting bad news on average. Panel B of Table 1 reports the contemporaneous Pearson correlation matrix for all variables. These correlations show E to be significantly and positively correlated with C, W and O, while showing C to be negatively correlated with W and D (note that because D is defined as depreciation multiplied by -1, cash flow from operations and depreciation is positively correlated). Finally, Panel C of Table 1 provides summary information on our volatility measures. Earnings volatility has a higher mean and dispersion (measured by standard deviation and range) across our sample than either cash flow volatility or working capital accruals volatility. This suggests that low/high E volatility firms tend to have low/high C and W volatility, implying that volatility in working capital accruals and cash flows are positively related.[8]

(iii) Model Estimation Results

Table 2 reports results from estimating model 1 for each earnings volatility quartile over the full sample period. Results in Panel A of Table 2 indicate a strong monotonic downward movement in estimated earnings coefficient and R^2 as earnings volatility increases, with earnings coefficient of 0.893 for the low earnings volatility quartile firms ($q = 1$) and 0.462 for the high volatility quartile ($q = 4$). These are consistent with the previous US findings of Dichev and Tang (2009) and confirm the relevance of questions about the possible drivers of such a negative relationship considered in section 3. In order to provide evidence on the extent to which the results may be driven by the other accruals variable O, Panel B reports results based on adjusted earnings excluding other accruals. These results continue to show a distinct (if somewhat

8 The correlation coefficient between C volatility and W volatility is 0.533 and significant at the 1% level, consistent with E volatility being positively correlated to C volatility and W volatility. The correlations between C and E volatility and W and E volatility were 0.386 and 0.293, respectively, both significant at the 1% level.

Table 1
Descriptive Statistics and Correlations

Panel A: Descriptive Statistics for Variables

Variables	*Means*	*Median*	*St. Dev.*	*Minimum*	*Q1*	*Q3*	*Maximum*
E	0.000	0.043	0.171	−1.178	−0.015	0.084	0.301
C	0.052	0.073	0.143	−0.863	0.012	0.126	0.387
W	0.009	0.006	0.066	−0.296	−0.018	0.036	0.298
D	−0.038	−0.032	0.031	−0.607	−0.049	−0.018	0.000
O	−0.023	−0.008	0.090	−1.122	−0.032	0.006	0.653

Panel B: Contemporaneous Correlations

Variables	*C*	*W*	*D*	*O*
E	0.731*	0.217*	0.012	0.574*
C		−0.235*	−0.208*	0.044
W			0.040	0.038
D				−0.019

Panel C: Summary Statistics for Volatility Measures

	Distribution for Whole Sample				*Mean Volatility for Quartiles based on Given Volatility Measure*			
Variables	*Mean*	*Median*	*St. Dev.*	*Range*	*Q1*	*Q2*	*Q3*	*Q3*
E Volatility	0.094	0.062	0.096	0.852	0.022	0.047	0.083	0.201
C Volatility	0.075	0.059	0.058	0.555	0.026	0.049	0.074	0.145
W Volatility	0.056	0.045	0.043	0.373	0.016	0.034	0.056	0.106

Note:
E denotes Earnings (WC01401 Pretax Income – WC01451 Income Taxes), *C* denotes cash flow from operations (WC04860 Net Cash Flow Operating Activities), *W* denotes working capital accruals (WC04825 Decrease/Increase in Receivables + WC04826 Decrease/Increase in Inventories – WC04827 Decrease/Increase in Accounts Payable), *D* denotes depreciation multiplied by −1 (WC04049 Depreciation and Depletion), and *O* denotes other accruals ($E – C – W – D$). All variables scaled by opening total assets (WC02999). Depreciation is multiplied by −1 so that *E* can be expressed simply as the sum of *C, W, D* and *O*.
*indicates statistical significance at the 1% level. Based on 16,847 firm-year observations during 1991–2010. *E* Volatility, *C* Volatility and *W* Volatility refer to the standard deviation of *E, C* and *W* for sample firms estimated over the number of years during 1991–2010 for which there are data for each sample firm. There were 575 firms per quartile based on total sample of 2,301 firms.

weaker) negative relationship between volatility and persistence, consistent (at least partly) with the Dichev and Tang (2009) view based on US data that the relationship is "rooted in the full sample" of firms and not driven simply by firms with volatile special items. Finally, results in Panel C show the higher estimated persistence of adjusted earnings across all firms and report full sample persistence estimates for both earnings measures lying within the corresponding quartile ranges reported in panels A and B.

Results from estimating model 2 are shown in Table 3. Panel A shows that coefficients associated with all four earnings components decline substantially and monotonically as we move from the lowest earnings volatility quartile ($q = 1$) to the highest earnings volatility quartile ($q = 4$). Differences in earnings component

Table 2
Estimation of Univariate Earnings Prediction Models for Earnings Volatility Based Quartiles

Earnings Prediction Model 1:
$E_{qt+1} = a_{1q} + a_{Eq}E_{qt} + \varepsilon_{t+1}$ *(Panel A)*
$X_{qt+1} = a_{1q} + a_{Xq}X_{qt} + \varepsilon_{t+1}$ *(Panel B) where "adjusted earnings" are* $X_{qt} = E_{qt} - O_{qt}$

Panel A: Results for Earnings Volatility Quartiles

	Intercept	a_{Eq}	*Adj.* R^2
$q = 1$ (low volatility)	0.005	0.893	0.796
	(8.36)	(119.12)	
$q = 2$	0.012	0.755	0.571
	(11.27)	(69.56)	
$q = 3$	0.003	0.695	0.473
	(1.759)	(57.21)	
$q = 4$ (high volatility)	−0.069	0.462	0.203
	(−16.60)	(30.44)	

Panel B: Results for "Adjusted Earnings" Volatility Quartiles

	Intercept	a_{Xq}	*Adj.* R^2
$q = 1$ (low volatility)	0.006	0.892	0.797
	(9.56)	(119.29)	
$q = 2$	0.009	0.809	0.660
	(10.49)	(83.98)	
$q = 3$	0.007	0.783	0.609
	(5.49)	(75.25)	
$q = 4$ (high volatility)	−0.109	0.668	0.457
	(−7.16)	(55.35)	

Panel C: Results for Full Sample

	Intercept	a_E *or* a_X	*Adj.* R^2
$E_{t+1} = a_1 + a_E E_t + \varepsilon_{t+1}$	−0.002	0.632	0.382
	(−1.55)	(94.90)	
$X_{t+1} = a_1 + a_X X_t + \varepsilon_{t+1}$	0.005	0.744	0.564
	(7.06)	(137.10)	

Note:
T-statistics reported in parentheses. Panels A and B are based on total sample of 16,847 firm-year observations over the period 1991–2010 divided into volatility based quartiles of approximately 4,200 firm-years each. Panel C is based on all 16,847 firm-year observations.

coefficients are relatively small for $q = 1$ firms, ranging from 0.911 for both a_{C1} and a_{D1} to 0.853 for a_{W1} and 0.761 for a_{O1}. These differences, however, widen for higher volatility quartiles due to differences in the rate of decline of earnings component coefficient estimates, the $q = 3$ ($q = 4$) estimates of 0.807 (0.692) for a_{C1}, 0.640 (0.435) for a_{W1}, 0.797 (0.186) for a_{D1} and 0.336 (0.093) for a_{O1} highlighting substantial differences in earnings component persistence estimates. As discussed in section 3, these results imply increasing differences in persistence of core earnings components for higher earnings volatility firms and/or differential downward bias due to the differential effect of transitory elements in the different earnings components.

Table 3

Estimation of Multivariate Earnings Prediction Models for Volatility Based Quartiles

Earnings Prediction Model 2:
$E_{qt+1} = a_{2q} + a_{Cq}C_{qt} + a_{Wq}W_{qt} + a_{Dq}D_{qt} + a_{Oq}O_{qt} + \varepsilon_{2qt+1}$

Panel A: Results for Earnings Volatility Quartiles

	Intercept	a_{Cq}	a_{Wq}	a_{Dq}	a_{Oq}	*Adj.* R^2
$q = 1$ (low volatility)	0.004	0.911	0.853	0.911	0.761	0.803
	(4.83)	(119.50)	(80.59)	(49.12)	(49.14)	
$q = 2$	0.005	0.818	0.700	0.800	0.509	0.598
	(3.44)	(72.81)	(40.91)	(26.83)	(24.66)	
$q = 3$	−0.006	0.807	0.640	0.797	0.336	0.523
	(−2.47)	(62.38)	(28.02)	(16.73)	(14.66)	
$q = 4$ (high volatility)	−0.106	0.692	0.435	0.186	0.093	0.290
	(−18.36)	(37.55)	(10.39)	(1.71)	(3.76)	

Panel B: Results for Cash Flow Volatility Quartiles

	Intercept	a_{Cq}	a_{Wq}	a_{Dq}	a_{Oq}	*Adj.* R^2
$q = 1$ (low volatility)	−0.018	1.051	0.507	0.935	0.188	0.417
	(−7.48)	(48.93)	(13.26)	(17.13)	(8.33)	
$q = 2$	−0.014	0.880	0.625	0.707	0.246	0.359
	(−5.23)	(43.01)	(19.70)	(13.00)	(10.78)	
$q = 3$	−0.025	0.874	0.649	0.656	0.175	0.410
	(−8.07)	(48.34)	(21.50)	(10.82)	(8.58)	
$q = 4$ (high volatility)	−0.053	0.732	0.560	0.292	0.264	0.410
	(−10.87)	(49.08)	(17.14)	(3.11)	(9.72)	

Panel C: Results for Working Capital Accruals Volatility Quartiles

	Intercept	a_{Cq}	a_{Wq}	a_{Dq}	a_{Oq}	*Adj.* R^2
$q = 1$ (low volatility)	−0.015	0.945	0.813	0.860	0.221	0.466
	(−6.77)	(54.17)	(13.35)	(18.98)	(10.32)	
$q = 2$	−0.020	0.873	0.725	0.611	0.253	0.478
	(−6.91)	(55.68)	(16.74)	(10.30)	(11.78)	
$q = 3$	−0.029	0.808	0.734	0.506	0.182	0.402
	(−8.25)	(47.35)	(19.90)	(7.20)	(8.08)	
$q = 4$(high volatility)	−0.036	0.752	0.514	0.498	0.278	0.409
	(−8.12)	(48.47)	(18.76)	(5.17)	(10.00)	

Note:
T-statistics reported in parentheses. Based on total sample of 16,847 firm-year observations over the period 1991–2010 divided into volatility based sub-samples of approximately 4,200 firm-years each.

Panels B and C of Table 3 provide evidence on the impact of cash flow volatility and working capital accruals volatility, respectively, on earnings component coefficient estimates in model 2. The results in Panel B highlight the impact of cash flow volatility on the coefficient estimates for cash flow itself, with a_{C1} and a_{C4} equal to 1.051 and 0.732, respectively. Similarly, the results in Panel C highlight the impact of working capital accruals volatility on the working capital accruals coefficient, with a_{W1} and a_{W4} equal to 0.813 and 0.514, respectively. Interestingly, while there is evidence in Panel C that the cash flow coefficient declines with increasing working capital accruals volatility, there is no evidence in Panel B that the working capital accruals coefficient declines with increasing cash flow volatility. The positive correlation between cash flow and working capital accruals volatility (see footnote 8) helps to explain why the cash flow coefficient might decline as working capital accruals volatility increases, as in Panel C. But the absence of a negative association between cash flow volatility and the working capital coefficient in Panel B is somewhat surprising.

Overall, we conclude that the results reported in Table 3 broadly support the relevance of a multivariate approach to analyzing the effect of volatility on earning prediction models, all panels indicating that volatility affects the relative magnitude of earnings component persistence estimates.[9] Given that comparison of the results in the three panels suggests that partitioning firms on earnings volatility reflects the effect of both cash flow and accruals volatility on model estimation, we now focus on the usefulness of the forecast models based on earnings volatility partitions as outlined in section 4(*i*).

(iv) Earnings Forecasting Results

Table 4 provides results for the QS, Q1 and FS forecast models outlined in section 4(*i*). Panel A provides mean parameter estimates for forecast models estimated recursively each year between 2000 and 2009 using 10 years of prior data (from which out-of-sample forecasts and forecast errors for each year during the period 2001 to 2010 are generated). The mean annual coefficient estimates, based on annual re-sorting of firms into earnings volatility quartiles and estimation of forecast models using 10 years of prior accounting data, are similar to the full sample estimates in Panel A of Table 3. Furthermore, annual coefficient estimates are broadly stable over time with most exhibiting relatively narrow estimation ranges.[10]

Panels B and C of Table 4 summarize our analysis of the forecast errors generated by QS, Q1 and FS forecast models. While a focus on absolute forecast errors provides an indicator of forecast model accuracy, forecasts based on core coefficients should also be unbiased. We therefore review results on bias in Panel B based on signed forecasts errors, before considering the main results on accuracy based on absolute forecast errors reported in Panel C.

Panel B reports mean and median signed forecast errors sorted on the percentage of positive forecasts errors. For the Q1 model, the percentage of positive (and negative) forecast errors falls in the 45%–55% range in 4 years and in these years the mean (median) forecast errors of −0.002 (0.001) are close to zero. However, in 5 other

9 We believe that these empirical results may reflect both "biased persistence" and "core persistence" explanations considered previously in the paper, as further discussed in sub-section 4(*iv*). Note also that if we assume the "biased persistence" story is correct, it is not possible to use the results in Table 3 to speculate convincingly on the relative severity of the impact of transitory elements in the different earnings components because of the complex impact of cross-correlations (both between earnings components and between transitory elements of components) on the biases in component persistence coefficients (as indicated previously in footnote 5). Assuming the "biased persistence" explanation is correct, we can only conclude that higher overall earnings volatility appears to be related to differing degrees of estimation bias in earnings component persistence coefficients.

10 An exception, however, is the depreciation coefficient in the QS model estimated for firms in the highest volatility, $q = 4$, which has a mean coefficient of −0.045 based on an annual estimated coefficient ranging from approximately 0.600 to −0.300. This negative coefficient is surprising (given that our depreciation variable is defined as a negative amount equal to −1 multiplied by the depreciation expense and hence would normally have a positive coefficient) and implies higher depreciation is related to higher future profits. This surprising effect appears to be associated with large negative intercept terms for these $q = 4$ firms which have a counterbalancing negative impact on future profit. It is not clear to us, however, why this should be the case.

Table 4

Forecast Errors Based on Alternative Multivariate Forecast Models

Panel A: Prediction Model Parameters Estimated Annually For Period 2000–09

		Intercept	a_C	a_W	a_D	a_O
Q1 Model (also QS Model for $q = 1$)	Mean	0.008	0.864	0.813	0.870	0.701
	Range	(0.010)	(0.136)	(0.193)	(0.151)	(0.460)
QS Model for $q = 2$	Mean	0.005	0.843	0.748	0.829	0.545
	Range	(0.007)	(0.079)	(0.047)	(0.094)	(0.377)
QS Model for $q = 3$	Mean	−0.002	0.771	0.623	0.741	0.318
	Range	(0.024)	(0.093)	(0.081)	(0.189)	(0.136)
QS Model for $q = 4$	Mean	−0.089	0.654	0.433	0.045	0.083
	Range	(0.064)	(0.038)	(0.089)	(0.956)	0.159
FS Model	Mean	−0.013	0.775	0.592	0.611	0.225
	Range	0.029	0.029	0.052	0.313	0.141

Panel B: Mean and Median Signed Forecast Errors by Percentage Positive Forecast Error

	Range for Percentage of Positive Forecast Errors	*Below 45%*	*45% to 55%*	*Above 55%*	*All (7,974) Forecast Errors*
Q1 Model	No. of years (avg % pos. errors)	5(39%)	4(51%)	1(60%)	10(46%)
	Mean forecast error	−0.026	−0.002	−0.001	−0.014
	Median forecast error	−0.010	−0.001	0.009	−0.004
QS Model	No. of years (avg % pos. errors)	2(43%)	3(49%)	5(61%)	10(54%)
	Mean forecast error	−0.034	−0.013	0.009	−0.006
	Median forecast error	−0.009	−0.002	0.011	0.003
FS Model	No. of years (avg% pos. errors)	–	3(49%)	7(64%)	10(60%)
	Mean forecast error	–	−0.030	−0.003	−0.009
	Median forecast error	–	−0.001	0.018	0.012

Panel C: Mean and median absolute forecast errors for period 2001-2010

		q = 1	*q = 2*	*q = 3*	*q = 4*	*All Firms*
	No. forecast errors	1,856	1,963	1,938	2,217	7,974
	QS Model	0.0347	0.0479	0.0664	0.1304	0.0726
	No. years lowest	9	5	4	0(0)	1(1)
Mean absolute forecast errors	Q1 Model	0.0347	0.0483	0.0670	0.1321	0.0735
	Exclude *O* for *q = 4*	–	–	–	0.1210	0.0703
	No. years lowest	9	4	4	0(2)	3(5)
	FS Model	0.0395	0.0513	0.0673	0.1162	0.0708
	No. years lowest	1	1	2	10(8)	6(4)

Continued

Table 4 (Continued)

Panel C: Mean and median absolute forecast errors for period 2001-2010

		q = 1	*q = 2*	*q = 3*	*q = 4*	*All Firms*
Median absolute forecast errors	QS Model	0.0157	0.0250	0.0364	0.0942	0.0373
	No. years lowest	10	4	5	0(0)	0(0)
	Q1 Model	0.0157	0.0253	0.0376	0.0759	0.0319
	Exclude O for $q = 4$	–	–	–	0.0705	0.0319
	No. years lowest	10	5	5	2(2)	7(7)
	FS model	0.0249	0.0309	0.0387	0.0656	0.0358
	No. years lowest	0	1	0	8(8)	3(3)

Note:
Panel A reports mean model parameters for prediction models estimated recursively each year from 2000 to 2009 using 10 years of prior data. For each year between 2000 and 2009, standard deviation of earnings for all firms over the previous 10 years are calculated and firms allocated to earnings volatility quartiles in order to estimate Q1 and QS forecast models. Range refers to the difference between the minimum and the maximum coefficient estimate from the ten regressions run for each model.
Panel B reports average mean and median signed forecast errors for each forecast model for years sorted into three groups according to the percentage of positive forecast errors i.e. below 45%, 45–55% and above 55%. In addition, the number of years out of the total of 10 forecast years falling into each of these groups are reported (and the average percentage of positive forecast errors shown in parentheses).
Panel C provides mean and median absolute forecast errors across the full 10 year forecast period from 2001 to 2010. The $q = 1$ to $q = 4$ columns provide the 10 year average of the mean or median absolute forecast errors for each forecast model. The final column gives the mean or median of all 7,974 forecast errors for each model generated over the period 2001 to 2010. For the Q1 model, forecast errors based on a constrained forecast model where the other accruals variable, O_{qt}, is set to zero are also reported for the $q = 4$ firms, together with the impact on the overall mean and median forecast errors for the Q1 model shown in the last column. Finally, the rows labeled "No. years lowest" gives the number of forecast years (out of a maximum total of 10) for which a given model provides the lowest mean or median forecast errors. The figures in parentheses refer to the relative performance of the models when the Q1 model forecasts exclude the O_{qt} variable for forecasts for firms in $q = 4$.

years when less than 45% of forecast errors are positive, mean (median) forecast errors of −0.026 (−0.010) are significantly below zero. The average mean (median) forecast errors of −0.014 (−0.004) for the full forecast period 2001–10 in the final column thus provide some evidence of negative bias in the forecast errors for this model. For the QS model, the average mean (median) forecast errors for the period 2001–10 of –0.006 (0.003) suggest low bias of the forecast errors for this model. However, the percentage of positive forecast errors was below 45% in 2 years, with corresponding mean (median) forecast errors of −0.034 (−0.009), and above 55% in 5 years, with corresponding mean (median) forecast errors of 0.009 (0.011). Finally, for the FS model, there are no years when the percentage of positive forecast errors was below 45% and 7 years when it was above 55%, suggesting a tendency for positive forecast errors for this model. The median forecast error of 0.012 for 2001–10 reinforces this conclusion, although the negative mean forecast error of −0.009 suggests the impact of some large negative forecast errors. In summary, we conclude that there is some evidence of bias in the forecast errors generated by all models but that the Q1 model generated forecast errors with low bias in 4 of the 10 years and the QS generated forecast errors over the full 10 year forecast period with low average bias.[11]

11 The 4 years when the Q1 model generated broadly unbiased forecasts (with average median forecast errors of just −0.001) lie between 2003–07 preceding the global financial crisis, while the following 2 crisis

Panel C of Table 4 summarizes the performance of the QS, Q1 and FS forecast models based on mean and median absolute forecast errors. The final column of Panel C provides overall results for the three models for all 7,974 firm-year forecast errors. This shows that the mean (median) absolute forecast error for QS, Q1 and FS forecast models are 0.0726 (0.0373), 0.0735 (0.0319) and 0.0708 (0.0358), respectively. The results based on mean absolute forecast errors do not provide convincing evidence of superiority for any one of the models. The results based on median absolute forecast errors, on the other hand, provide evidence in favour of the superior accuracy of the Q1 model, the Q1 model providing not only the lowest median absolute forecast error for the full sample of 7,974 forecast errors but also the lowest median absolute forecast error in 7 out of the 10 forecast years. Also reported in the final column of Panel C are the absolute forecast errors for the Q1 model when O, other accruals, is assumed to be zero for the highest volatility firm quartile, $q = 4$. As discussed more fully below, such an assumption is consistent with the logic of the Q1 model and has the effect of reducing the overall mean absolute forecast error for the Q1 model from 0.0735 to 0.0703 (but has no effect on the median error of 0.0319 for the Q1 model). We now consider the results for the volatility-based firm quartiles reported in the columns of Panel B of Table 4 labeled $q = 1$ to $q = 4$ in greater detail.

For firms in the low volatility quartile $q = 1$, both mean and median absolute forecast errors strongly support the superiority of QS/Q1 model (for $q = 1$ firms, these forecast models are identical) over the FS forecast model. More specifically, the mean (median) error of 0.0347 (0.0157) for the QS/Q1 model is equal to 88% (63%) of the mean (median) error of 0.0395 (0.0249) for the FS model. In addition, the QS/Q1 model provides both lower mean and median forecast errors than the FS model in 9 of the 10 forecast years between 2001 and 2010. These results confirm that, at least for low volatility firms, a forecasting approach conditioned on volatility is superior to a full sample approach. This is consistent with the view that for $q = 1$ firms the estimated coefficients in the Q1/QS forecast model are relatively accurate estimates of underlying core earnings component persistence (and the earnings components themselves are relatively free of transitory elements).

Results for firms in the mid-volatility quartiles, $q = 2$ and $q = 3$, provide less convincing evidence of superiority for any of the forecast models. For $q = 2$, there is no evidence of any significant difference in mean or median absolute forecast errors between Q1 and QS models but some evidence that these models are superior to the FS model. In relation to the latter, the median results provide the strongest evidence of superiority of the Q1 and QS models over the FS model, median absolute forecast errors for both Q1 and QS models amounting to approximately 80% of the 0.0309 figure reported for the FS model and the FS model providing the lowest mean and median forecast errors in only 1 of the 10 forecast years. For $q = 3$, neither mean nor median absolute forecast errors indicate significant differences between the three

years, 2008 and 2009, resulted in substantial negative median forecast errors of −0.012 in both years. The QS model, on the other hand, had positive forecast errors above 55% in 4 years with an average median forecast error of 0.011 between 2003–07 and slightly negative average median forecast errors of −0.003 in 2008 and 2009. Finally, the FS model had positive forecast errors above 55% with a large average median forecast error of 0.016 in all years 2003–07 and a substantially lower average median forecast error of 0.008 in 2008 and 2009. A possible interpretation is that the Q1model is unbiased and the QS and FS models are pessimistic in the more "normal" period prior to the crisis and that the financial crisis led to the large negative forecast errors for the Q1 model in 2008 and 2009 and the apparently lower bias of the QS and FS in those years.

forecast models, although again the FS model was the worst performer in most forecast years. The results for these mid-volatility firms therefore cannot be interpreted as supporting the greater accuracy of the QS model implied by the "core persistence" perspective but equally do not support the superiority of the Q1 model based on the "biased persistence" perspective. A possible explanation is that the Q1 forecast model coefficients are better estimates of core earnings component persistence than the QS forecast model coefficients for $q = 2$ and $q = 3$ firms but that transitory elements in reported earnings components undermine the performance of the Q1 model (as indicated in our discussion of scenario 2 in section 4(i), any transitory elements contained in C_{qt}, W_{qt}, D_{qt} and O_{qt} will reduce the quality of the Q1 model forecasts of earnings at date $t + 1$). Another possible explanation is that higher volatility is associated with both lower core persistence and downward estimation bias such that neither model dominates the other.

Finally, results for firms in the highest volatility quartile, $q = 4$, provide support for the superiority of the Q1 model over the QS model (particularly when O, the other accruals variable, is excluded from the Q1 model) but interestingly also show that the FS model performs best for these high volatility firms. The superior performance of the FS forecast model is reflected both in terms of the lowest mean (median) forecast errors of 0.1162 (0.0656) over the full 10 year period and in terms of the lowest mean and median forecast errors in 8 out of the 10 forecast years. The QS and Q1 forecast models have similar mean absolute forecast errors of 0.1304 and 0.1321, respectively, when the O variable is included in the Q1 model but the mean absolute forecast error of the Q1 model improves to 0.1210 when O is excluded i.e. when the Q1 model is constrained to be:

$$Forecast\left[E_{qt+1}\right] = a_{21} + a_{C1}C_{qt} + a_{W1}W_{qt} + a_{D1}D_{qt}.$$

The rationale for constraining the Q1 model is simply that the "biased persistence" perspective suggests that the low regression coefficient for O_{qt} reported in Table 3 Panel A for $q = 4$ firms may be due to the presence of sizeable transitory elements in this variable. The median error for the "full" Q1 model of 0.0759 for these firms is substantially lower than the median of 0.0942 for the QS model and this performance improves further to 0.0705 when the O variable is excluded.

Overall, the results reported in Panel C of Table 4 provide support for the view that the Q1 forecast model, based on the lowest earnings volatility quartile of firms, provides earnings forecasts that are at least as accurate on average as the QS model based on the volatility quartile to which a firm belongs or the FS model based on the full sample of firms. Thus, while differences between the models are not great in terms of the mean absolute forecast errors recorded in the last column of Panel C, the Q1 model generated median absolute forecast errors substantially below the other two models. The detailed quartile results show that Q1 and QS forecast models are of equivalent accuracy for $q = 1$, $q = 2$ and $q = 3$ firms and superior to the FS model for these firms. The equivalence of the Q1 and QS models for these firms may be due to the effect of transitory elements in current earnings components used to predict future earnings "counteracting" the superior accuracy of the Q1 forecast model coefficients. Alternatively, it may be due to the joint effect of lower true persistence coefficients and downward estimation bias for $q = 2$ and $q = 3$ firms rendering neither approach superior. The superiority of the Q1 model over the QS model for

$q = 4$ firms suggests that, for high volatility firms, the substantially lower forecast model coefficients used by the QS model may be significant underestimates of the core coefficients (consistent with the "biased persistence" perspective on the negative association between persistence and volatility discussed in section 3). However, the superior performance of the FS model over the Q1 model for these firms also may imply lower core persistence for these firms than that implied by the Q1 (consistent in part with the "core persistence" perspective on the negative persistence/volatility relationship).

5. SUMMARY AND CONCLUSIONS

This paper has built on previous US evidence of a negative relationship between earnings volatility and earnings persistence. We have presented an analytical framework highlighting the possible roles of downward estimation bias and lower core earnings persistence in such a relationship and considered the implications for earnings forecasting. Following this, we have provided empirical evidence for the UK in relation to the impact of earnings volatility on forecast model estimation and carried out an empirical comparison of the forecasting performance of alternative volatility-related earnings forecast models based on our analytical framework.

Our empirical results based on estimation of univariate earnings forecast models over the period 1991–2010 are broadly consistent with the previous US evidence. In addition, the evidence on how earnings volatility affects cash flow and accruals coefficients in multivariate forecast models highlighted differences in these coefficients for higher volatility firms. Further evidence showed the separate impact of cash flow volatility and working capital accruals volatility on estimation of earnings forecast models, implying the possible role of both economic events and accounting measurement issues in the negative relationship between earnings volatility and earnings persistence.

Our analysis of the impact of the negative relationship between earnings volatility and earnings (component) persistence on out-of-sample forecasting focused on two distinct volatility-based forecast models, as well as a full sample based model. The results for UK firms over the period 2001–10 using median absolute forecast errors indicated greater accuracy for the Q1 model. This finding lends support to the implicit assumption underlying this model that lower persistence associated with higher volatility firms is at least in part due to downward estimation bias. The superior performance of the FS (full sample) model for the highest volatility firms, and the approximately equivalent performance of QS (quartile specific) and Q1 models for firms of average volatility, however may suggest the presence of both downward estimation bias and lower core persistence.

In conclusion, we interpret our results as supporting the view that transitory elements in both cash flow and accrual components of earnings are at least partly responsible for the results in this paper and may also help to explain the previous US results reviewed in section 2.[12] The relatively strong performance of the Q1 forecast

12 Dichev and Tang (2009) do not explicitly consider the issue of biased persistence estimates and do not use volatility based information to make earnings forecasts as in the current paper. However, we do not believe that their additional analysis beyond that briefly reviewed in section 2 of this paper is inconsistent

model occurred despite the use of reported (rather than "core") cash flow and accruals components. Thus, it is possible that forecast accuracy may be substantially further improved by identification of the transitory elements in current reported earnings components. Following from this, an implication of our empirical results for accounting policy making is that there may be benefits to investors from further improving the reporting and/or disclosure of transitory items in financial statements. Finally, our results highlight the potential for improvement in investor earnings forecasting by management accounting choices aimed at smoothing the effect of transitory fundamental performance.[13]

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with our analysis. For example, in their Table 7 (p. 177), they report results that future earnings for current high earnings/low volatility firms are significantly higher than future earnings for current high earnings/high volatility firms (and, interestingly, that this was not anticipated in analysts' earnings forecasts). This could be consistent with such high earnings/high volatility firms having *either* lower core earnings persistence *or* larger positive transitory earnings than the high earnings/low volatility firms.

13 A stock price based analysis by Tucker and Zarowin (2006) provides empirical evidence to support the informativeness of income smoothing consistent with this conclusion.