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The prediction of future cash flow for UK private companies

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ABSTRACT
UK private companies follow less stringent reporting standards than public ones. Despite extensive research on public companies' financial reporting, little has been done for private firms, especially in the UK. We conducted prediction error tests on about 1.5 million observations on UK private companies from 2006–2022, distinguishing between the different classes of private companies: micro, small, medium-sized, and large. We found that errors in predicting future cash flow one period ahead for micro and small companies were only slightly larger than those of public companies. For medium-sized and large private companies, the errors were more than double, suggesting less informative disclosures. These results are robust for predicting beyond the next period and for times when financial distress is high. The impact of regulatory revisions for private companies in 2016, based on International Financial Reporting Standards for Small and Medium-sized Companies, is minor.

KEYWORDS
Prediction of future cash flow; financial reporting regulation; private companies

Introduction

One of the major changes in UK financial reporting in recent years has been the emergence of separate reporting regimes for different classes of private companies, permitting them to follow less stringent reporting standards than public companies. The class of a company is defined according to a combination of the size measures of the company: total turnover, total assets, and number of employees. A significant milestone was the introduction of The Financial Reporting Standard for Smaller Entities (FRSSE) in 1997. Its main thrust was to providesmaller companies with simplifications of the UK financial reporting measurement rules used for public companies.

The relaxation of financial reporting then took on an international dimension. The International Accounting Standards Board (IASB) issued its International Accounting Standard for Small and Medium-sized Entities (International Accounting Standards Board [IASB], 2009).[1] In addition, there were developments from the European Union; the EU Directive 2012/6

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[1]Public companies from 2005 were required to adopt International Financial Reporting Standards.

(European Union, 2012) recognized a new class of small company, the micro company, and the EU Directive 2013/34 (European Union, 2013) had the objective of reducing disproportionate costs imposed on smaller companies. In response to these developments, the standards for private companies in the UK were significantly revised and became effective in 2016. They are contained in Financial Reporting Standard 102 covering small, medium-sized, and large private entities (Financial Reporting Council, 2015a) and Financial Reporting Standard 105 covering the very small micro entities (Financial Reporting Council, 2015b). These standards (with periodic revisions) are currently applicable in the UK.

FRS 102 continues and extends the approach of the FRSSE but places the regulations within the context of the IASB and European approaches. In particular, it states that the benefits derived from the information should exceed the cost of providing it, which gives the company significant discretion (Financial Reporting Council, 2015a, section 2.13). FRS 105 covers micro entities and further simplifies asset and liability measurement relative to FRS 102. An important and new feature of FRS 105 is that the accounts are presumed to give a true and fair view if they comply with the standard (Financial Reporting Council, 2015b, section 3.2). This contrasts with the earlier FRSSE in which supplementary disclosures were sometimes necessary when compliance with the standard did not necessarily suffice. The new feature reflects the considerable simplicity of the standard, which may have otherwise led to the cost savings on transaction measurement being swamped by extra disclosure costs.

When private companies adopt recognition and measurement standards that are less rigorous than those for public companies, an important concern is the effects on the quality of financial reporting. The relaxation may eliminate the disproportionate cost of reporting, as suggested by the EU, but an important issue remaining is whether there is also a disproportionate reduction in the usefulness of the information provided, so that users' needs are not satisfied. We assess this issue by evaluating the ability of private company reporting to provide information about future cash flow. This is a well-established approach for public companies. It is also appropriate for private companies since both FRS 102 and FRS 105 are based on the IFRS for SMEs and predicting a company's future cash flow is a key objective in the IASB's Conceptual framework (International Accounting Standards Board [IASB], 2018, paragraph 1.3). In addition, apart from owners and stakeholders such as customers and employees, the prospect for future cash flow is of particular importance for private companies in view of their reliance on bank finance.

Despite the need to assess the impact of the relaxation of reporting requirements, there is a lack of research on predicting the cash flow of private companies. A notable exception to this is Hope et al. (2017) who find that the accruals of U.S. firms are informative about future cash flow. The scarcity of private company research in this area is especially important in view of their significant proportion of economic activity and the relative paucity of information about the companies' prospects outside of the financial reporting cycle. Research in this area is particularly lacking in the UK.

In this study, we assess the prediction of UK private companies' future cash flows from their accounting data. We use the predictions for public companies as a benchmark since they are regulated by the more complex International Financial Reporting Standards (IFRS). The predictions for both private and public companiesare based on the current value of aggregate cash flows, accruals, and capital expenditures, which is the approach adopted in public company studies. We use the same model specification for both private and public companies to identify more accurately the effect of the relaxation in the measurement rules for private companies. We also investigate the separate role of accruals and discretionary accruals to gain insight into the factors behind the results. The focus of the current study is to establish, in light of the long-standing relaxation of rules for private companies, whether their reporting is effective in predicting future cash flow. We do not investigate whether tightening regulations might be a suitable remedy if the errors are higher than acceptable. Our objective is to report the effectiveness of financial reporting in predicting future cash flow. The key results are outlined next.

Our study is based on about 1½ million private company observations over the period 2006–2022. We find that the prediction error for micro companies is lower than for other classes of private companies, and only 30 percent higher than of public companies. Despite the reduction in the reporting burden on micro companies, their information seems useful for predicting future cash flow. Small private companies have only a slightly higher prediction error than micro companies. However, medium-sized and large private companies have an error that is more than double that of public companies. Given that these are substantial companies with extensive stakeholder interests, the quality of reporting may need to be reviewed.

The introduction of FRS 105 for micro companies and FRS 102 for all other private companies in 2016 was a major shift in reporting regulations. Our research is the first to evaluate the predictive value of the change. The two new standards were based on the International Financial Reporting Standard for Small and Medium-sized Entities instead of the previous UK regulations designed for public companies. Overall, the 2016 regulation resulted in little change. The overall prediction error for micro companies rose slightly, but they still have the smallest prediction error compared to other private companies. The overall error for small companies decreased, and the errors for medium and large companies were unchanged. An important policy issue is the option for smaller private companies to file a cutdown version of the full accounts with the Registrar of Companies; this is the version that is available to the public. We find that exercising the option leads to more prediction errors, which is consistent with the objective of the recent Economic Crime and Corporate Transparency Act 2023 designed to remove some of these options.

The structure of the paper is as follows. In the next section, we outline the motivation for the work and the distinctive features of our approach. Section three provides details of the prediction models and error metrics. This is followed by the sample selection process and the descriptive statistics of the variables. Section five presents our key results, comparing groups of private companies (micro, small, medium-sized and large) with public companies, and distinguishing between the contribution made by past cash flows, accruals, and discretionary accruals to forecast accuracy. Section six provides supplementary and robustness tests, and the final section concludes.

Motivation and approach

The importance of future cash flow

The prospective value and risk of future cash flow to the company is a key objective of financial reporting, and understanding the directors' stewardship of the company's resources is critical to stakeholders in assessing future cash flow. This is recognized in the IASB's recent revision of the Conceptual Framework, which is the basis of both public and private company financial reporting regulation.

> 1.2 The objective of general purpose financial reporting is to provide financial information about the reporting entity that is useful to existing and potential investors, lenders and other creditors in making decisions relating to providing resources to the entity. (IASB, 2018, Extract from page A15)
>
> 1.3 The decisions described in paragraph 1.2 depend on the returns that existing and potential investors, lenders and other creditors expect. . . . Investors,' lenders' and other creditors' expectations about returns depend on their assessment of the amount, timing and uncertainty of *(the prospects for) future net cash inflows to the entity* and on their assessment of management's stewardship of the entity's economic resources. Existing and potential investors, lenders and other creditors need information to help them make those assessments. (IASB, 2018, Extract from page A15, emphasis added)
>
> 1.16 Information about a reporting entity's past financial performance and how its management discharged its stewardship responsibilities is usually *helpful in predicting the entity's future returns on its economic resources*. (IASB, 2018, Extract from page A17, emphasis added)

The literature on the prediction of public company future cash flow from accounting numbers is therefore, not surprisingly, considerable. One of the main areas is the evaluation of how informative current cash flows are about future cash flows and the additional contribution of accruals (see for example, Ball & Nikolaev, 2022; Barth et al., 2016; Habib, 2010; Nallareddy et al., 2020; Mulenga & Bhatia, 2017). A related issue is whether any predictive ability has diminished over time, given the well-publicized view that financial information has become outdated and does not reflect the current importance of intangible assets (Kim & Kross, 2005). Alongside these studies is work concerned with predicting stock returns, which serve as a proxy for future cash flow (Ball et al., 2016). Other areas have a narrower focus, for example, whether discretionary accruals and the smoothness of earnings have an impact on the prediction of future cash flows (Badertscher et al., 2012; Tucker & Zarowin, 2006), and whether cash flows and accruals are informative about future material misstatements (Dechow et al., 2011).

This research is evidence of the substantial demand for financial information about public companies. It is therefore surprising that there are very few studies about the prediction of the future cash flow of private companies, especially given the importance of the annual report relative to other sources of information about the company. Hope et al. (2017) give a comprehensive background to the stakeholder demand theory for information about the future cash flows of private companies. However, a few additional remarks are also worthwhile.

An important component of the demand for private company accounting information is that it provides information for lenders about future cash flow, which will repay the debt. But to fully understand this demand, it needs to be placed in the context of all the lending technologies for SME finance; see Berger and Udell (2006) for a comprehensive review. One of their key observations is that when company reporting is opaque, other lending technologies are available. For example, a subset of the firm's assets may be pledged as collateral, which is then the primary repayment source rather than future cash flow. In addition, there may be other ways to identify the credit worthiness of the company, say for example, relationship lending whereby soft information is gathered over time by the loan officer; more recently, research shows that online reviews may be used as evidence (Huang, 2024).

However, despite the availability of these substitutes, there appears to be a substantial demand for private company accounting information that can signal future cash flow. Minnis and Shroff (2017) report, in their survey of regulators and private company managers, that lenders and creditors are among the top beneficiaries of private company financial reporting. This finding is consistent with the evidence of both Bharath et al. (2008) and Hellman et al. (2022), who report a reduction in the cost of debt for private companies following increased disclosure. A key point here is that the substitute lending technologies may be more costly (or less effective) than those based on forward-looking accounting information. This interpretation is supported by Huang (2024), who finds that the impact of online reviews is smaller when banks have more information. Breuer et al. (2018) suggest an explanation for the switch to hard financial-reporting-based transactional banking. They argue that it benefits companies by reducing their reliance on the subjective opinions of loan officers. On the banking side, it reduces their costs by transferring them to companies and also reduces the information asymmetries between banks, allowing increased competition. It also facilitates the enforcement of banking contracts (MacLeod, 2007).

Stakeholders apart from lenders and creditors may also value the information in the annual report and accounts. Private companies can be large organizations[2] with employees, customers, and suppliers who have little knowledge of the economic condition of the business. Cheney (2012) reflects the considerable stakeholder demand for forward-looking cash flow information when commenting on the FASB's framework for private company reporting. Apart from the demand from lenders and creditors, there is demand for information within a private company. For example, accounting information, and particularly cash flow information, is important for managerial purposes (Collis & Jarvis, 2002a); also, the annual report and accounts may be useful in reducing any information asymmetry between owners, particularly those who are not members of the same family (Collis et al., 2004).

Given all these well-documented demands for private company financial reporting, it is important to understand the impact of the simpler standards applied to UK private companies and in particular the 2016 regulation change.

A focus on prediction

A distinctive feature of our tests is to make prediction a specific focus. One aspect of this is that we use out-of-sample tests; i.e., the data used to calculate the predicted value excludes the cash flow realization used to calculate the prediction error. This is a more realistic approach than the in-sample tests undertaken by much of the cash flow prediction literature. Although in-sample tests are likely to have greater statistical power and therefore may be preferred to out-of-sample tests (Inoue & Kilian, 2005), parameter instability from one period to another often offsets this advantage (Clark & McCracken, 2005). This is consistent with other studies that document that economic variables exhibit substantial parameter instability from one period to another (Pitarakis, 2017; Poon & Granger, 2003; Rapach & Wohar, 2006). Therefore it is important that tests of the predictive sufficiency of financial reporting

[2]For example, a small company in the UK may have up to 50 employees.

should reflect the real position of stakeholders, i.e., trying to predict out-of-sample future cash flow from prior data.

A related aspect of our prediction focus concerns how we measure the effectiveness of the predictor variables. We measure the size of the prediction error. The vast majority of prior studies run a regression model with the future value of cash flows as the dependent variable; the size and significance of the coefficients then provide some evidence about the predictive usefulness of the variables. However, the impact of an explanatory variable on future cash flow depends not only on the coefficient but also on the size of the variable. The coefficient may be statistically and economically significant, but if the value of the variable is relatively small, then it may have very little effect on predicting future cash flow.

Disaggregation of private companies into micro, small, medium, and large

An important issue we address that was not considered in prior studies is the heterogeneity among private companies. Private companies are exceptionally varied, ranging from a single-owner consultancy business to a nationwide privately owned industrial operation. In order to understand the potential range of outcomes within the private company sample, the firm-year observations are divided into groups according to the different reporting regimes for micro, small, medium, and large according to the legislation[3] at the time. This contrasts with prior work, which groups private companies all together.

The partition of the sample by reporting regime is important for understanding and evaluating financial regulation, but it also reflects the interests of stakeholders. They make assessments in very broad brush ways; see for example, Bouwman et al. (1995) and Breton and Taffler (2001). The regimes are based on a combination of size measures. Since stakeholders will have an impression of a company's approximate size, our classification and findings are also likely to be useful to them.

Forecasting models and prediction error measures

Forecasting models

We follow the prediction model of Lev et al. (2010), which they use to predict the cash flow of public companies for the following period. We also use this model for our private company predictions, so the prediction errors between private and public companies reflect the differences between the measurement procedures of the different financial reporting regimes. An important aspect of

[3]Micro companies were first defined by The Small Companies (Micro-Entities' Accounts) Regulations 2013. Private company observations before this date are classified as Micro according to this legislation. Details of the classifications are given in the Appendix.

their approach is that they use capital expenditure as an independent variable to predict future cash flows (since the expenditure increases the scale of operations) in addition to the usual cash flows and accruals. The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*-1 and the cash flow in period *t*. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t*. This is a realistic test of the information contained in key accounting numbers about future cash flow. Our forecast construction, following Lev et al. (2010), does not contain control variables. Instead, we estimate the models at the two-digit SIC code industry level so that industry specific influences are reflected in the estimated coefficients.

The purpose of the analysis is to establish whether stakeholders of private companies have been put at a disadvantage (in prediction terms) due to the less stringent standards that the companies are allowed to follow. By disadvantage, we mean in comparison with the accounting standards that public companies are required to use. Therefore, the forecast errors for public companies are based solely on their accounting information and do not include other information, which is available for public companies outside of the accounts (for example, the reports by analysts and other financial intermediaries).[4]

We estimate three models. Model 1 (the full model) uses cash flow and individual accruals to predict future cash flow; this is the main model. Model 1, estimated at each industry level, is given in Equation (1).

$$\begin{aligned} CFO_t = {} & a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} \\ & + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + u_t \end{aligned} \quad (1)$$

Where the variables (scaled by opening total assets) are:

CFO_t	= the cash flows from operations for period *t;*
ΔRec_{t-1}	= the change in receivables during period *t*-1;
ΔInv_{t-1}	= the change in inventory during period *t*-1;
ΔPay_{t-1}	= the change in payables during period *t*-1;
$\Delta DTax_{t-1}$	= the change in deferred tax during period *t*-1;
ΔOth_{t-1}	= the change in other accruals during period *t*-1;
$D\&A_{t-1}$	= the depreciation and amortization for period *t*-1;
CAP_EX_{t-1}	= the capital expenditure for period *t*-1;
u_t	= a random residual.

[4]In fact, there would be little point in including this information since it is well established that it contains bias and has a very short term focus. See or example, Dimson and Marsh (1984), DeBondt and Thaler (1990) and Bradshaw (2011).

We then use these estimated coefficients[5] to calculate the predicted cash flowfor period $t+1$ (Predicted$_{t+1}$) from the accounting data at time t. This is calculated as in Equation 1a. The prediction error is then calculated by subtracting the predicted value from the realization, as follows.

$$\mathrm{Predicted}_{t+1} = \widehat{a} + \widehat{b}.\mathrm{CFO}_t + \widehat{c}.\Delta\mathrm{Rec}_t + \widehat{d}.\Delta\mathrm{Inv}_t + \widehat{e}.\Delta\mathrm{Pay}_t + \widehat{f}.\Delta\mathrm{DTax}_t + \widehat{g}.\Delta\mathrm{Oth}_t, \widehat{h}.\mathrm{D\&A}_t + \widehat{j}.\mathrm{CAP\_EX}_t \tag{1a}$$

Prediction $\mathrm{Error}_{t+1} = \mathrm{Actual}_{t+1}$ (the realization) minus the predicted value $= \mathrm{CFO}_{t+1} - \mathrm{Predicted}_{t+1}$

Model 2 (the nondiscretionary accruals model) uses cash flow and total accruals to make predictions, but with the discretionary component removed. These accruals are the result of future events expected by the company's management. For example, the value of inventory for sale may be written down in anticipation of a decline in future prices. Thus, the discretionary accruals can both inform or mislead stakeholders and therefore form an important component of reporting quality. A comparison of Model 2 with Model 1 identifies the impact of discretionary accruals; if discretionary accruals are informative, then when they are removed in Model 2, the average error will be larger compared with Model 1.[6] Model 2 (prediction without discretionary accruals) are constructed in the same way as Model 1, except the equation to estimate the coefficients is given in Equation (2). Discretionary accruals are calculated with the model of Kothari et al. (2005).

$$\mathrm{CFO}_t = \mathrm{a} + \mathrm{b}.\mathrm{CFO}_{t-1} + \mathrm{c}.\mathrm{ACC}_{t-1} - \mathrm{DA}_{t-1} + \mathrm{d}.\mathrm{CAP\_EXP}_{t-1} + \mathrm{u}_t \tag{2}$$

where:

$\mathrm{ACC}_{t\text{-}1}$= Accruals for period t-1

$\mathrm{DA}_{t\text{-}1} = \Delta\mathrm{Rec}_{t\text{-}1} + \Delta\mathrm{Inv}_{t\text{-}1} + \Delta\mathrm{Pay}_{t\text{-}1} + \Delta\mathrm{DTax}_{t\text{-}1} + \Delta\mathrm{Oth}_{t\text{-}1} + \mathrm{D\&A}_{t\text{-}1}$ $\mathrm{DA}_{t\text{-}1}$

= discretionary accruals, calculated by the Kothari et al. (2005) method, which is the residual from the regression, estimated at the industry level,

$$ACC_t = \alpha_0 + \frac{\alpha_1}{Assets_{t-1}} + \alpha_2.\Delta Revenue_t + \alpha_3.PPE_t + \alpha_4.ROA_t + e_t$$

Model 3 (the cash flow model) uses cash flow only to make predictions. Comparison of errors from Model 3 with those from Model 2 identifies the impact of nondiscretionary accruals; if nondiscretionary accruals are

[5]If a coefficient in the regression is not significant at 5 percent, it is set to zero in the calculation stage.

[6]We assume that the effect of aggregating individual accruals has a small effect on the error relative to discretionary accruals.

informative, then Model 3 will have larger errors than in Model 2. A comparison of errors from Model 3 with those from Model 1 identifies the impact of total accruals; if total accruals are informative, then Model 3 will have larger errors compared with Model 1. The coefficients used for Model 3 are estimated from Equation (3).

$$\mathrm{CFO_t} = \mathrm{a} + \mathrm{b.CFO_{t-1}} + \mathrm{c.CAP\_EXP_{t-1}} + \mathrm{u_t} \tag{3}$$

Prediction error measures

We calculate the prediction error metrics used in Lev et al. (2010) for comparison. These are the mean of signed forecast error, the mean absolute forecast error, the average of the adjusted R^2 from yearly regressions of actual values on predicted values, and the annual average of Theil's U statistics.

The weakness of these measures, for our purposes, is that the errors are scaled by lagged assets. There are two problems with this approach. First, the forecast error as a proportion of the size of the business is not a conventional and intuitive measure that regulators and stakeholders might find useful; a more typical measure of error is its relation to the realization. Second, any comparison between companies is affected by both the prediction error and the intensity with which assets are used in the business; a forecast error as a proportion of lagged assets may be large simply because the company has a low value of assets. In particular, this may affect the comparison between private and public companies since the former may be less capital intensive at the same level of earnings.[7]

For our main analysis, we use a summary measure of prediction errors, which is not affected by the capital intensity effect. The method we use is to scale errors by the realization of future cash flows so both the numerator and the denominator are scaled by lagged assets, making the error proportionate to the realization of future cash flows. In this way, the capital intensity effect is excluded from the error measure. The measures we use are the mean proportionate error (MPE) and the mean absolute proportionate error (MAPE), and these are defined as follows:

$\mathrm{PE_t}$ = the proportionate error for company i, from aforecast at t.

$$= \frac{Actual_t - Predicted_t}{Actual_t}$$

$\mathrm{MPE_t}$ = the mean proportionate error from aforecast at t,

$$= \frac{\sum_{i=1}^{n} PE_i}{n}$$

[7]For example, in our sample the ratio of earnings to assets (for positive cash flow) is 0.063 for public companies but 0.30 for private companies, indicating that private companies have a lower intensity of assets for a given level of earnings.

APE_t = the absolute proportionate error for company i, from a forecast at t.

$$= \left| \frac{Actual_t - Predicted_t}{Actual_t} \right|$$

$MAPE_t$ = the mean absolute proportionate error from a forecast at t,

$$= \frac{\sum_{i=1}^{n} APE_i}{n}$$

The MAPE is used in many fields (see, for example, Morley et al., 2018) and allows comparison between groups of observations. A well-known limitation of the MAPE measure is that the mean is over-influenced by extreme observations. They can arise due to small values of the realization in the denominator and lead to a skewed distribution of errors since MAPE has a lower bound of zero but no upper bound. Methods to deal with the issue proliferate (for example: Hyndman & Koehler, 2006; Morley et al., 2018; Swanson et al., 2000; Tofallis, 2015). However, since the mean reflects both the central tendency and dispersion aspects of the forecast errors, it may, in fact, be a very suitable way of summarizing the prediction errors for our purposes. Potential stakeholders and regulators need to know the variety of prediction errors that might arise; hence, values on the outer edge of the distribution for a group of companies may be useful. In this paper, we use the mean (MAPE) but support it with information about the median (MedAPE), which can easily be interpreted, and the standard deviation.

The absolute prediction errors of private and public companies have a number of properties that make it difficult to select an acceptable significance test of the difference between the MAPE values: the sample variances may be unequal; and the samples are bounded at zero and hence likely to result in substantial deviations from normality. Either of these issues leads to difficulties in selecting the appropriate significance test. Furthermore, the effectiveness of tests varies with the difference in variances, the degree of departure from normality, and the difference in sample size between the groups. In addition, assessing the extent of the difference in variances or deviations from normality prior to the selection of an appropriate test, in a two-stage procedure, may bring its own statistical power issues, leading to erroneous conclusions. These issues are discussed in Zimmerman (2011), Lantz (2013), and Delacre et al. (2019).

Given these difficulties in selecting one of the standard significance tests, we construct the sampling distribution from the sample data using the approximate randomization (permutation) method discussed in Noreen (1989) and Wilcox (2003). We measure the observed difference in MAPE between the two samples, n1 and n2. Next we select n1, and then n2, observations at random (without replacement) from the combined sample, and measure difference between the two means. Repeating this 10,000 times gives the sampling distribution of the difference between the means when there is no difference between them (since observations are selected randomly from the same combined sample). The observed difference between the sample means is compared with this distribution in the usual way.

Sample selection and descriptive statistics of variables

Sample selection

The data applied in this paper are obtained from the "Financial Analysis Made Easy" (FAME) database supplied by Bureau Van Dijk. The database provides financial statement information for both public and private UK companies. The main advantage of the FAME database is that it contains comprehensive accounting data for privately held corporations and is a common source of data for work in this area (Ball & Shivakumar, 2005; Dedman et al., 2014).

We select both private and public companies for the period of 2006–2022[8] from FAME. Table 1 (Panel A) shows our sample selection criteria for firms. We begin with companies with a known asset value in any year; this gives 898,998 private firms and 1,770 public firms. We exclude banks, other financial institutions (SIC codes 6000-6799), and firms with negative total assets. The sample is also restricted to public companies that explicitly report under IFRS and private companies that explicitly report under UK GAAP. We require companies to report a profit and loss account, which is needed to construct the cash flow forecast. This leaves 327,252 private companies and 1,357 public companies with the required variables in any of the years in the sample period, and gives 1,564,641 firm-year observations for private companies and 14,269 observations for public companies. As expected, the average number of firm-year observations[9] for private companies is approximately five, whereas it is 10 for public companies; this difference reflects the relatively short lives of private companies. Panel A also shows the number of firm-year observations and the number of firms for the different classes of company: public, micro, small, medium-sized, and large. The generally observed inverse relation between company size and risk is apparent from the ratio of firm-year observations to the number of firms. Micro and small companies have the lowest ratios, while those for medium-sized and large private companies are larger, reflecting their relative longevity.

Our sample size of some 1,564,641 observations on 327,252 private companies is comparable with other studies. Hope et al. (2013) have approximately 40,000 observations; Hope et al. (2017) have approximately 66,000 observations; and Ball and Shivakumar (2005), the standard study of UK private companies 1989–99, has approximately 115,000 observations.[10] However,

[8]We also need prior year data to calculate accruals, but this is not part of our sample period for the forecast tests.
[9]Defined as the number of firm year observations divided by the number of firms with available variables.
[10]The study starts with around 130,00 observations, but after problems concerning the availability of cash flow data and other issues, the sample is reduced (Ball & Shivakumar, 2005, pp. 99, 102).

Table 1. Sample selection and type of firms.

	Public # of Firms	Private # of Firms
Panel A: Sample selection		
Firms with known value of total assets between 2006–2022	1,770	898,998
Firms excluding financial service industry	1,369	784,181
Public companies reporting under IFRS GAAP	1,369	
Private companies reporting under UK GAAP		783,780
Firms with available variables in period *t*	1,357	327,252
Micro		171,276
Small		72,286
Medium		56,782
Large		26,908
Firm-year observations		
Public	14,269	
Total Private		1,564,641
Micro		723,369
Small		305,771
Medium		352,912
Large		182,589

		Mean	P10	P25	Median	P75	P90
Panel B: Sales and Total Assets for different size of firms (figures in '000)							
Public	Sales	1,891,003	1,384	9,479	64,190	467,403	2,346,100
	Assets	931,457	3,784	14,082	77,376	547,607	3,007,203
All Private	Sales	25,771	12	60	608	9,338	31,387
	Assets	19,460	8	42	877	7,880	31,143
Micro	Sales	156	4	19	64	182	421
	Assets	313	4	12	44	188	895
Small	Sales	3,464	834	1,276	2,439	4,577	7,001
	Assets	7,200	506	967	2,266	5,633	23,543
Medium	Sales	15,996	6,309	8,977	13,445	20,157	27,898
	Assets	12,972	3,936	5,540	8,467	13,840	27,547
Large	Sales	221,983	29,381	40,720	67,020	139,766	342,899
	Assets	150,459	17,149	25,231	49,370	134,071	447,572

Type of firm is defined by regulatory reporting regimes based on size thresholds from the Companies Act 2006.

the number of observations varies with the length of the sample period. Consequently, the size of the sample companies is also a useful comparison to make and is given in Table 1 (Panel B). The mean values of sales and assets indicate that there is large variation across the classes of companies; public companies have much larger assets than large private companies, by a factor of six. In turn, large private companies have larger assets than small companies by a factor of 20, which is the reason why the different classes of private companies should be analyzed separately.

In comparison with the size of companies in Hope et al. (2017, Table 2)[11] our sample contains both smaller and larger companies. The median value of total assets in our sample is £0.877 m smaller than their $4.079 m, indicating that our distribution is well to the left of theirs. But the mean value in our sample is £19.46 m, larger than their value of $8.79 m reflecting the larger

[11]Hope et al. (2013) do not give data on total assets, but in other respects the sample appears to be similar to their 2017 one. For example, the mean values of LogAssets are very close (1.559 and 1.586).

Table 2. Descriptive statistics of variables used to construct forecasts.

	N	Mean	Std. Dev.	p10	Median	p90
Public						
CFO	14,269	0.005	0.217	−0.321	0.049	0.241
ΔWC		0.002	0.085	−0.111	0.002	0.108
ΔRec		0.012	0.045	−0.037	0.002	0.076
ΔInv		0.007	0.026	−0.015	0.000	0.043
ΔPay		0.008	0.034	−0.030	0.002	0.055
DTax		0.001	0.002	0.000	0.000	0.001
D&A		0.048	0.044	0.001	0.037	0.114
ΔOth		−0.068	0.100	−0.209	−0.050	0.039
CAP EX		0.091	0.145	0.004	0.030	0.299
ΔWC-DA		0.002	0.036	−0.031	−0.001	0.033
All Private						
CFO	1,564,641	0.112	0.327	−0.263	0.063	0.693
ΔWC		0.017	0.258	−0.255	0.001	0.333
ΔRec		0.010	0.092	−0.081	0.000	0.118
ΔInv		0.004	0.028	−0.015	0.000	0.032
ΔPay		0.005	0.051	−0.047	0.000	0.067
DTax		0.002	0.007	0.000	0.000	0.005
D&A		0.025	0.037	0.000	0.008	0.081
ΔOth		−0.032	0.252	−0.328	−0.014	0.254
CAP EX		0.059	0.146	0.002	0.022	0.155
ΔWC-DA		0.017	0.063	−0.053	0.013	0.083

Type of firm is defined by regulatory reporting regimes based on size thresholds from Companies Act 2006.
CFO is defined as cash flow from operations scaled by beginning total assets. ΔWC is defined as changes in working capital excluding cash and short-term debts, scaled by beginning total assets. ΔRec is defined as changes in accounts receivables scaled by beginning total assets. ΔInv is defined as changes in inventories scaled by beginning total assets. ΔPay is defined as changes in accounts payables scaled by beginning total assets. DTax is defined as deferred tax scaled by beginning total assets. D&A is defined as depreciation and amortization, scaled by beginning total assets. ΔOth is calculated as ΔWC – (ΔRec + ΔInv – ΔPay)—DTax—D&A. Capex is defined as capital expenditures scaled by beginning total assets. ΔWC-DA is defined as changes in working capital discretionary accruals, scaled by beginning total assets. DA is defined as discretionary accruals, which are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2 \Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$, where $Accr_{i,t}$ is total accruals, measured as the change in noncurrent assets minus the change in current noninterest-bearing liabilities, minus depreciation and amortization for firm *i* at period *t*, scaled by beginning total assets; *ΔRev* is the annual change in revenue scaled by beginning total assets; *PPE* is property, plant and, equipment scaled by beginning total assets; *ROA* is the return on assets. The residuals are discretionary accruals (DA). The variables are winsorized at the 1 percent level.

companies covered in our sample. Overall, these comparisons indicate that our sample captures a range of companies suitable for the research issues.[12]

Descriptive statistics of variables used to construct forecasts

Next, we provide details of the variables used to construct the forecasts. Table 2 shows the summary statistics of the variables used in the study. As is common practice, the variables are scaled by lagged assets.

The values in Table 2 for public companies are comparable with those in the study of public companies by Lev et al. (2010, p. 791)[13]; for example, our mean capital expenditure (CAPEX) for public companies is 0.091, which is comparable with their value of 0.070. However, there are

[12]Ball and Shivakumar (2005, p. 104) give the mean value of total assets as £3.7 m. However, apart from the inflation issue, this is based on companies prior to their removal from the sample due to lack of data for the tests.
[13]Lev et al. (2010) follow a slightly different procedure to the norm and scale by total assets rather than lagged total assets.

differences in the cash flow variable (CFO). The variation in our sample is larger (our standard deviation is 0.217 compared with their 0.129). The mean cash flow in our sample is 0.005 compared with their value of 0.066 This suggests that a greater proportion of our sample reflects public companies, which are less able to generate cash flow from their assets. However, at the top end of the cash flow distribution, the samples are more alike; our p90 value is 0.241 compared with their Q3 value of 0.136.

The mean cash flow for private companies, 0.112, in Table 2 is similar to the value, 0.109, in Ball and Shivakumar (2005, Table 1). These values are larger than those for public companies, which may indicate that private companies are more cash-based undertakings relative to their asset size. Consistent with expectations, the mean capital expenditure is larger for public companies (0.091) than for private companies (0.059). These comparisons with prior research suggest that our sample is a sound basis for understanding the predictive value of private and public company reporting.

Results: The predictive ability of cash flow and accruals

This section gives our main results. First, we compare our results with the study of public companies by Lev et al. (2010), on which our forecasting models are based. Second, we analyze the forecast errors with our preferred metric, the mean absolute proportionate error (MAPE). We examine the errors from all three prediction models: the full model (Model 1); the model without discretionary accruals (Model 2); and the model without any accruals (Model 3). We then investigate the impact of the regulatory changes in 2016, in which the financial reporting for private companies was revised and covered in two new standards, FRS 102 and FRS 105. These new standards are based on the IFRS for SMEs, whereas the prior regulations were modifications of standards previously designed for public companies. The final analysis concerns the effect of options available to some private companies to file a cutdown version of the accounts with Companies House, with the full accounts being available only to shareholders.

Comparison with Lev et al. (2010)

In this section, we examine the mean prediction error (MER) and the mean absolute prediction error (MAER) for public companies, comparing with Lev et al. (2010). Our values are given in Table 3, columns 1&2.

Table 3. Descriptive statistics: prediction error of forecasts.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	MER	MAER	R^2	Theil's U	MPE	MAPE	sd. MAPE
Model 1							
Public	−0.001	0.083	0.393	0.562	0.367	0.895	1.068
Micro	0.012	0.221	0.169	0.684	0.470	1.142*	1.109
Small	0.001	0.182	0.086	0.817	0.731	1.310*	1.428
Medium	0.000	0.117	0.085	0.812	0.596	1.856*	2.167
Large private	−0.002	0.122	0.078	0.833	0.694	1.890*	2.100
Model 2							
Public	−0.001	0.068	0.333	0.418	0.358	0.641†	0.667
Micro	0.020	0.190	0.147	0.439	0.315	1.054†	1.087
Small	0.005	0.164	0.088	0.623	0.707	1.174†	1.181
Medium	0.002	0.111	0.073	0.713	0.601	1.654†	1.873
Large private	0.000	0.115	0.063	0.724	0.659	1.606†	1.742
Model 3							
Public	−0.001	0.065	0.299	0.445	0.390	0.565‡	0.481
Micro	0.015	0.219	0.102	0.641	0.434	1.179‡	1.190
Small	0.000	0.177	0.030	0.790	0.690	1.234‡	1.333
Medium	0.000	0.114	0.021	0.779	0.581	1.885‡	2.250
Large private	−0.002	0.120	0.018	0.805	0.692	2.063‡	2.295

Type of firm is defined according to regulatory reporting regimes from the Companies Act 2006.

Model 1: $CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.DA_{t-1} + j.CAP\_EXP_{t-1} + u_t$

Model 2: $CFO_t = a + b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + u_t$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2 \Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$

Model 3: $CFO_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + u_t$; where CAP_EXP_{t-1} is used as the control variable.

The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*-1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.

All statistics are computed after winsorizing the top 1 percentile.

MER is defined as the mean of signed forecast error from the pooled sample. MAER is defined as the mean absolute forecast error from the pooled sample. MPE is defined as the mean of proportionate error by removing the scaling factor. MAPE is defined as the mean of absolute proportionate error by removing the scaling factor. R^2 is defined as the average of the adjusted R^2 from yearly regressions of actual values on predicted values over the sample period (2006–2022). Theil's U is defined as the average of yearly U statistics. U is defined as the square root of $\sum(\text{actual-forecast})^2/\sum(\text{actual})^2$.

* indicates a significant difference between each type of private company and public company is significant at a 5 percent level or better.

†indicates a significant difference between model 1 and model 2 for each type of company is significant at a 5 percent level or better.

‡indicates a significant difference between model 1 and model 3 for each type of company is significant at a 5 percent level or better.

The MAER in Model 1 for public companies is 0.083 in our study and 0.054 in Lev, Li, Sougiannis (Table 2, Year 1, Model 5), indicating that the forecasts in our sample are comparable. The MER in Model 1 for public companies is −0.001 in our study compared with their 0.001, suggesting that there are more negative errors in our sample. The R^2 between predicted and actual values (in column 3 of Table 3) also suggests that our study is comparable with theirs; our study gives 0.393 compared with their 0.58. The Theil U values (in column 4 of Table 3) are similar, 0.562 compared with their 0.53.

Overall, the MAER results from Model 1 in Table 3 show that private companies have larger errors than public companies; for example, the MAER for micro companies is 0.221 compared with 0.083 for public companies. Within private companies, the MAER for micro companies is larger than for small companies (0.182), which in turn is larger than those for medium-sized and large private companies (0.117 and 0.122, respectively). This pattern of results is approximately replicated in Model 2 and Model 3. These results may give support to those who question the relaxation of reporting standards for smaller companies. However, although the MER and MAER values are consistently scaled, a difficulty of interpretation is that they are scaled by lagged assets. This introduces a bias, discussed above, which increases the prediction error for companies that have a small asset base relative to their earnings. To avoid this issue, in the next section we use our preferred measure, the prediction errors scaled by the realization.

The mean proportionate and mean absolute proportionate error (MPE and MAPE)

In this section, we compare the prediction errors across public and private companies using the mean absolute proportionate error (MAPE), so errors are proportionate to the realization. Our first research question (RQ1) is as follows:

RQ1: Are the prediction errors of private companies, following less stringent accounting standards, different from those of public companies?

The proportionate prediction errors for public and private companies are given in Table 3. Column 5 shows the mean proportionate error (MPE), and column 6 shows the mean absolute proportionate error (MAPE). Comparing these results with columns 1&2 shows the size of the bias when the errors are scaled by lagged assets. Whereas the MAER for micro companies (column 2) is more than double that of public companies, the MAPE is less than 30 percent higher (1.142 compared with 0.895).

This result supports the relaxation of reporting standards for micro companies; although the MAPE is larger than that for public companies, the difference is small. Importantly, micro companies have smaller errors than other private companies; for example, the MAPE for micro companies is 1.142 while the MAPE for large private companies is 1.890. Small companies are similar to micros and have a MAPE of 1.310. Thus, it appears that despite the less stringent standards followed by micro and small companies, their reporting has nearly as much predictive value as that of public companies. This is accompanied by their relatively low standard deviations of the absolute prediction errors in column 7 of Table 3 (1.109 for micros and 1.428 for small companies compared with 1.068 for public companies). Based on the generally observed inverse relationship between company size and its variability, we would not expect this type of performance from micro and small companies.

For example, Meeks and Whittington (2023) document the high survival rate of UK public companies since 1948, and Gaio and Henriques (2018) show the greater risk of SMEs relative to other companies in the European Union.

The consistency of our results with the inverse size-risk relation is indicated in Table 1 (Panel A), where we use the ratio of the number of firm-year observations to the number of firms as a measure of longevity and risk. Public companies have the highest ratio and micro/small companies have the lowest. There are a number of potential explanations for this consistency. One concerns the financial literacy of the owners based on Riepe et al. (2022), who argue that financial literacy is associated with risk aversion. Collis and Jarvis (2002a), and Collis (2012) find that there is a high level of financial literacy among the management of small private companies; 31 percent have a qualified accountant, and 67 percent of directors have business training. Corroborating this, Peel (2016) finds that survival of small companies is strongly associated with the education of the management.

A second explanation relates to the fact that micro and small companies are largely funded by debt. This means that when economic circumstances are challenging, the required interest payments give them very little room for maneuver, and they exit the sample far quicker than larger businesses. For the small business, risk doesn't mean reduced profits, it means liquidation. This is supported by evidence in Peel (2016) and Andreeva et al. (2016), who find that gearing is an important determinant of failure in small companies. Thus, micro and small companies in our sample are observed prior to the impact of any economic problems.

Simple financial reporting may also bring benefits to managers and stakeholders alike. Reduced regulation may allow management to spend more time running the business rather than complying with complicated regulations, as suggested by Sorrentino and Smarra (2014). Support for this explanation is provided by Collis and Jarvis (2002b, Table 9), who report that directors believe that the preparation of the statutory accounts misallocates management time. Collis and Jarvis (2002b, Table 8) and Collis (2008, Table 6.1) find from postal surveys and interviews that statutory accounts are used as a general check on the information that management uses to run the business. Given this background use, the simpler reporting for micro and small businesses may facilitate this corroboration. Thus, overall, the business may be managed more effectively. Finally, the result for micro and small companies is consistent with the wide-ranging theory of "less is more" (Aikman et al., 2014; Gigerenzer, 2004). The hypothesis in our context is that current performance is the result of a mix of permanent and transitory factors. While a simple prediction approach may omit a number of permanent factors, its advantage is that it is less likely to capture those that are transitory and irrelevant for prediction. Thus, the simple regulations for micro and small businesses may be sufficient.

In contrast, medium-sized and larger private companies have prediction errors and standard deviations that are more than double that of public companies. One possible explanation is that these companies are subject to more risk than other companies (public or private). This is supported by the relative large standard deviations of MAPE, which are double that for public companies. Consequently, more complex recognition and measurement regulations may be appropriate for these companies.

The role of discretionary accruals and total accruals in predicting future cash flow

In this section, we narrow our focus and analyze the impact of total accruals and discretionary accruals on the prediction error. The accruals principle in reporting is an important correction to the cash flow as a measure of performance. For example, revenue from company sales is recognized in the profit and loss account at the time of the sale, and not at the later time of payment, which gives rise to holding transactions. These accruals are the result of a current event in the company and are nondiscretionary. There are also some accruals that are the result of future events expected by the management of the company. For example, the value of inventory for sale may be written down in anticipation of a decline in future prices. These are the discretionary accruals that can both inform or mislead stakeholders and therefore form an important component of reporting quality (see for example, Salma & Bhuiyan, 2024).

The calculation of discretionary accruals is that proposed by Kothari et al. (2005, Equation 7). The measure is the difference between reported total accruals and nondiscretionary accruals, which are estimated from the accounting variables of the company; the estimate is constructed during the period the prediction is made and at the industry level. Model 2 excludes discretionary accruals when estimating the parameters for cash flow predictions and is given in Equation (2) . If discretionary accruals are informative for predicting future cash flow, then the MAPE from Model 2 will be larger than those in Model 1. Our second research question (RQ2) is therefore as follows:

RQ2: Are the discretionary accruals of private companies, following less stringent standards, as informative about future cash flow compared with those of public companies?

In Table 3, we find that for all classes of private companies, our estimates of discretionary accruals are not informative for predicting the next period's cash flow; the MAPE values for Model 2 are statistically smaller than those in Model 1. Discretionary accruals are not informative about future cash flows, and moreover reduce the accuracy of the prediction.

This is consistent with the widely held belief that earnings management is rife. However, some caution is needed since the findings may have more to do with the model that estimates the discretionary accruals. For example, studies by Gerakos (2012) and Ball (2013) call in to question the models used to estimate discretional accruals; in particular, they both make the point that estimates of discretionary accruals rely on an imperfect understanding of nondiscretionary accruals, a comment that is particularly pertinent in the case of private companies. It is also important to set the findings in context. The lack of information in the discretionary accruals of private companies is much the same for public companies; the relaxation of reporting standards for private companies does not appear to make private companies very different from public companies in this respect.

We next assess the effect of total accruals on the prediction errors. Accruals measurement is a central aspect of accounting procedures. It is therefore important to assess its effect on the predictability of future cash flow. The study by Hope et al. (2017) finds that accruals and accruals quality are significant variables in a regression to explain future cash flow. However, as we argue above, a weakness of this approach is that the significance and size of the coefficients do not map directly in to the change in the prediction error. Our research question is as follows:

RQ3: Are the accruals of private companies, following less stringent standards, as informative about future cash flow compared with those of public companies?

We measure the effect of total accruals by comparing predictions based on Model 3 (using cash flow and capital expenditure alone) with those from Model 1 (using cash flow, individual accruals, and capital expenditure). If total accruals are informative, then the errors from Model 3 will be larger than those for Model 1.

For micro, medium-sized, and large private companies, the MAPE values for Model 3 are larger than those for Model 1. This suggests that their accruals are informative about future cash flow. In contrast, small companies have a lower MAPE value for Model 3 in comparison with Model 1, indicating that accruals convey more noise than signal about future cash flows. However, not too much should be made of this result since the reduction, although statistically significant, is very modest, 1.234 in Model 3 compared with 1.310 in Model 1. Accruals of private companies are more informative than in the case of public companies for which Model 3 has a much smaller prediction error (0.565) than Model 1 (0.895). We do not investigate this result here, but it is comparable with Nallareddy et al. (2020), who report that, for US public companies, 1989–2015, accruals and its components have a very small incremental predictive ability over cash flows.

The effect of the private company regulatory changes in 2016

The year 2016 was significant for the financial reporting regulation of private companies. The Financial Reporting Standard for Smaller Entities (FRSSE) was withdrawn and FRS 102 (covering small, medium, and larger private companies), and FRS105 (covering micro companies) became mandatory. These new standards are based on the IFRS for SMEs, whereas the prior regulations were modifications of standards previously designed for public companies.[14] In this section, we assess the impact of this significant change in regulation. Our research question is as follows.

RQ4: What is the impact of the regulatory regime changes for private companies in 2016?

The results are shown in Table 4, giving key prediction error statistics pre-2016 and post-2016 for all three models; the significance tests in the final column show, for each model, whether the MAPE in the post-2016 period is significant from that in the pre-2016 period.

The values for MAPE for Model 1 show that in the period 2016–2022, the prediction error rose slightly for micro companies, from 1.110 in the pre-2016 period to 1.234. There was a relaxation in standards for micro companies, switching from the FRSSE to FRS 105; the FRSSE was an abbreviated version of UK standards for all companies, whereas FRS 105 is based on the International Financial Standard for Smaller Entities (IFRS for SMEs). The purpose of the switch was to ease the disproportionate burden of financial regulation. It results in a slight rise in the MAPE, but micro companies have the lowest MAPE of all private companies, both before and after 2016.

In the case of small companies, the pre/post-2016 breakdown is especially relevant, since Table 3 shows that they are the only group of private companies for which total accruals are not informative about future cash flow. The results in Table 4 show that this characteristic is more pronounced in the post-2016 period. The predictive superiority of the cash flow model (Model 3) over the full model (Model 1) is 0.056 in the pre-2016 period, but double that (0.105) in the post-2016 period.[15] In the cases of medium and large private companies, the regime changes are consolidatory in nature since their MAPE values are not significantly different pre-2016 and post-2016.

[14]In 2005, public companies were required to adopt International Financial Reporting Standards.
[15]The reduction in MAPE for Model 3 compared to Model 1 is 0.056 (1.267–1.323) in the pre-2016 period, but 0.105 (1.188–1.293) in the post-2016 period.

Table 4. Proportionate error of forecasts before and after regulatory changes in 2016.

	Pre-2016 (Year 2006–2015)		Post-2016 (Year 2006–2015)	
	MPE	MAPE	MPE	MAPE
Model 1				
Public	0.372	0.911	0.362	0.875
Micro	0.448	1.110	0.530	1.234*
Small	0.734	1.323	0.728	1.293*
Medium	0.605	1.862	0.583	1.847
Large private	0.687	1.899	0.704	1.878
Model 2				
Public	0.355	0.652	0.361	0.631
Micro	0.291	1.031	0.406	1.140†
Small	0.712	1.192	0.699	1.148†
Medium	0.611	1.669	0.589	1.637†
Large private	0.645	1.629	0.679	1.591†
Model 3				
Public	0.396	0.577	0.382	0.550‡
Micro	0.412	1.151	0.494	1.261‡
Small	0.689	1.267	0.691	1.188‡
Medium	0.593	1.923	0.566	1.836‡
Large private	0.689	2.132	0.697	1.959‡

Type of firms is defined according to regulatory reporting regimes from the Companies Act 2006.
Model 1: $CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + u_t b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + u_t$

Model 2: CFO $_t = a +$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2 \Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$

Model 3: CFO $_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + u_t$; where CAP_EXP_{t-1} is used as the control variable.
The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*-1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.
All statistics are computed after winsorizing the top 1 percentiles.
MPE is defined as the mean of proportionate error by removing scaling factor. MAPE is defined as the mean of absolute proportionate error by removing scaling factor.
*indicates a significant difference between pre-year-2016 and post-year-2016 for each type of company within Model 1 is significant at a 5 percent level or better.
†indicates a significant difference between pre-year-2016 and post-year-2016 for each type of company within Model 2 is significant at a 5 percent level or better.
‡indicates a significant difference between pre-year-2016 and post-year-2016 for each type of company within Model 3 is significant at a 5 percent level or better.

The option for private companies to file non-full accounts

Private companies are sometimes permitted to file, for public access, a cutdown version of their regular accounts, which are then available only to shareholders. This was an early concession to some private companies in the Companies Act 1981. Government policy now is to eliminate these options, since companies need to provide the full information for their shareholders, and, consequently, there is little cost savings. In this section, we investigate the effect filing of non-full accounts on the prediction errors. FAME identifies whether full accounts have been filed, and we use their records in the test.[16] The research question is:

[16]Note that we do not test for all the filing options. In order to construct a forecast, we require all our sample companies to have filed a profit and loss account, i.e., not to have exercised any option not to do so.

RQ5: Do the options for some private companies to file non-full accounts decrease predictive ability?

The results are given in Table 5, distinguishing between pre-2016 and post-2016 regulation changes and also between the different classes of private companies. The significance tests show the differences between MAPE values for companies filing non-full accounts compared to those filing full accounts.

One key result is that in both periods, the prediction errors are significantly larger for those companies not filing full accounts. For example, in the pre-2016 period for Model 1, the MAPE for micro companies is 1.059 for those filing full accounts but 1.158 for those that did not, a difference of 0.099. For small companies, the difference between pre/post-2016 periods is very small, although statistically significant. For medium-sized private companies, the difference is larger; for full filing companies, the MAPE is 1.843 but 1.988 for those that did not, a difference of 0.145.

Another important finding is in the differences in the impact of non-full filing between pre/post 2016. For micro companies, there is not much change between the two periods (0.099 and 0.101). There is a general reduction in prediction error for small and medium-sized private companies. In the case of small private companies, the difference in the post-2016 period is even smaller (0.008) than in the pre-2016 period (0.023). Despite the reduction for medium-sized companies, the impact of post-2016 is still sizable (0.111). This effect of non-full filing for micro and medium-sized companies supports the view of the Economic Crime and Corporate Transparency Act 2023, that the options to file non-full accounts hinder informative reporting and should be withdrawn.

Supplementary tests

We undertake a number of supplementary tests to check the robustness of our findings. We undertake the Heckman adjustment for selection bias, since only those companies with sufficient data to construct predictions are included. We also analyze predictions for two and three periods ahead, as stakeholders are interested in these cash flows too. Finally, we investigate the predictive quality of financial reporting in companies that have a high probability of financial distress. This is an important issue, since it is in these circumstances that informative financial reporting for private companies is at a premium, because there is little other public information about the companies' prospects.

The effect of the Heckman adjustment for selection bias

The tests in the previous sections are based on companies with the necessary data. As a result, as we show in Table 1, more than half of private

Table 5. Full accounts vs non-full accounts during the period of regulation changes for micro, small, and medium-sized firms.

	Model 1			Model 2			Model 3		
	MPE	MAPE	diff	MPE	MAPE	diff	MPE	MAPE	diff
Pre-2016 (Full Accounts)									
Micro	0.43	1.059		0.27	0.994		0.389	1.088	
Small	0.724	1.315		0.705	1.185		0.682	1.263	
Medium	0.598	1.843		0.606	1.661		0.585	1.891	
Pre-2016 (Non-Full Accounts)									
Micro	0.467	1.158	0.099*	0.314	1.067	0.073†	0.437	1.211	0.123‡
Small	0.752	1.338	0.023*	0.727	1.204	0.019†	0.702	1.275	0.012
Medium	0.652	1.988	0.145*	0.658	1.731	0.070†	0.646	2.132	0.241‡
Post-2016 (Full Accounts)									
Micro	0.516	1.19		0.396	1.094		0.504	1.225	
Small	0.723	1.29		0.697	1.145		0.689	1.19	
Medium	0.58	1.841		0.585	1.635		0.562	1.83	
Post-2016 (Non-Full Accounts)									
Micro	0.541	1.291	0.101*	0.412	1.206	0.112†	0.481	1.308	0.083‡
Small	0.731	1.298	0.008	0.7	1.155	0.01	0.696	1.183	−0.007
Medium	0.624	1.952	0.111*	0.651	1.667	0.032	0.628	1.922	0.092

Type of firm is defined according to regulatory reporting regimes from the Companies Act 2006.

Model 1: $CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + u_t$

Model 2: $CFO_t = a + b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + u_t$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2\Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$

Model 3: $CFO_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + u_t$; where CAP_EXP_{t-1} is used as the control variable.

The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*-1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.

Full accounts are firms that filed full accounts to companies' houses. Non-full accounts are firms that take the advantage of exemptions in disclosures.

All statistics are computed after winsorizing the top 1 percentiles.

MPE is defined as the mean of proportionate error by removing scaling factor. MAPE is defined as the mean of absolute proportionate error by removing scaling factor.

diff is the difference of MAPE between full and non-full accounts within each model and each type of company.

*, †, ‡ indicate the difference is significant at 5 percent level or better.

companies are excluded in this process. One of the reasons why companies may lack the necessary data is that they may reduce disclosure in order to minimize any predatory behavior of competitors (Bernard, 2016; Bernard et al., 2018; Minnis & Shroff, 2017). To adjust for this selection bias, we use the usual Heckman (1979) two-stage adjustment procedure whereby the inverse Mills ratio is calculated from a probit model of the selection equation and inserted into the estimation models (Equations 1–3). A major disadvantage of the Heckman procedure is that it may significantly reduce the sample further because of the additional variables needed to estimate the selection equation. This is often the reason why OLS estimation is preferred for the main results, leaving the robustness section to check that the selection bias has had little effect on the estimated coefficients; see for example, Ball and Shivakumar (2005, p. 117). We follow this approach, and recalculate the results in Table 3 with the selection bias

Table 6. Selection bias and endogeneity for private firms.

	Model 1			Model 2			Model 3		
	MPE	MAPE	*MAPE (Table 3)*	MPE	MAPE	*MAPE (Table 3)*	MPE	MAPE	*MAPE (Table 3)*
Micro	0.517	1.01	*(1.142)*	0.391	0.923	*(1.054)*	0.488	1.018	*(1.179)*
Small	0.759	1.295	*(1.310)*	0.728	1.185	*(1.174)*	0.736	1.193	*(1.234)*
Medium	0.598	1.845	*(1.856)*	0.603	1.651	*(1.654)*	0.581	1.871	*(1.885)*
Large private	0.694	1.864	*(1.890)*	0.656	1.577	*(1.606)*	0.692	2.06	*(2.063)*

Type of firm is defined by regulatory reporting regimes based on size thresholds from the Companies Act 2006.

Model 1: $CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + k.InverseMills + u_t$.

Model 2: $CFO_t = a + b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + e.InverseMills + u_t$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2\Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$.

Model 3: $CFO_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + d.InverseMills + u_t$; where CAP_EXP_{t-1} is used as the control variable.

Inverse Mills is estimated, following Heckman (1979), from a probit model with size (defined as log of total assets), leverage (debts to assets ratio), growth (in sales), and operating cycle as preditors; estimates of probit model are used to compute the Inverse Mills ratio, which is included in Model 1 – Model 3 as the control for selection bias and endogeneity.

The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*-1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.

All statistics are computed after winsorizing the top 1 percentiles.

MPE is defined as the mean of proportionate error by removing scaling factor. MAPE is defined as the mean of absolute proportionate error by removing scaling factor. MAPE in parentheses are from Table 3 for comparison only.

adjustment. The results are given in Table 6, showing the Table 3 MAPE value in brackets.

The MAPE values in Table 6 for all classes of private companies and across all models are slightly smaller than in Table 3; this reflects the smaller and data-rich sample in Table 6. However, all the results are qualitatively similar to Table 3. Micro companies have the lowest MAPE values relative to other private companies. When discretionary accruals are excluded, in Model 2, the prediction errors are reduced slightly (relative to Model 1) for all classes of private companies, suggesting that discretionary accruals are not informative for prediction purposes. Other results of Table 3 also remain. For micro, medium-sized, and large private companies, the prediction error is larger (relative to Model 1) when total accruals are excluded in Model 3 (cash flow only), indicating that accruals are informative. Also, as in Table 3, this result does not hold for small companies since the MAPE value decreases in Model 3, but the errors in all small company models are well below those for medium-sized and large private companies.

Prediction for horizons beyond one year

The above analysis focuses on the prediction of next period's cash flow, in common with many studies of public companies. In this section, we examine

Table 7. Proportionate errors for horizons beyond one year.

	Model 1		Model 2		Model 3	
	MPE	MAPE	MPE	MAPE	MPE	MAPE
Year 2 prediction						
Public	0.41	0.67	0.379	0.489	0.423	0.45
Micro	0.456	1.066	0.324	0.997	0.431	1.109
Small	0.691	1.241	0.658	1.093	0.669	1.225
Medium	0.561	1.714	0.56	1.542	0.552	1.781
Large private	0.67	1.851	0.612	1.528	0.67	2.015
Year 3 prediction						
Public	0.43	0.692	0.404	0.506	0.44	0.478
Micro	0.481	1.091	0.347	1.019	0.458	1.131
Small	0.697	1.284	0.668	1.136	0.68	1.29
Medium	0.563	1.738	0.559	1.557	0.554	1.808
Large private	0.671	1.929	0.614	1.562	0.676	2.1
Year 1 + 2 + 3 prediction						
Public	0.435	1.04	0.455	1.074	0.508	1.072
Micro	0.629	1.565	0.621	1.47	0.654	1.631
Small	0.378	1.783	0.227	1.727	0.394	2.003
medium	0.398	1.951	0.423	1.853	0.413	2.154
Large private	0.548	2.077	0.533	1.903	0.57	2.312

Type of firm is defined according to regulatory reporting regimes from the Companies Act 2006.

Model 1: $\mathrm{CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + u_t}$

Model 2: $CFO_t = a + b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + u_t$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2\Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$

Model 3: $\mathrm{CFO_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + u_t}$; where $\mathrm{CAP\_EXP_{t-1}}$ is used as the control variable.

The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t)* the relationship between accounting numbers for period *t*−1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.

Year 2 (or year 3) predictions follows the same prediction procedure described above with one difference: the cross-sectional estimate and forecast involve a two-year lag (or three-year lag). Year 1 + 2 + 3 prediction are based on the procedures described above, except the single-year free cash flows on the left-hand side of each prediction model are replaced by the aggregated future cash flows of *t* + 1, *t* + 2, and *t* + 3.

All statistics are computed after winsorizing the top 1 percentiles.

MPE is defined as the mean of proportionate error by removing scaling factor. MAPE is defined as the mean of absolute proportionate error by removing scaling factor.

predictions beyond one year ahead, since the IASB's Conceptual Framework talks about future cash flow in general and not just about the immediate future. When predicting two periods ahead, we follow a similar procedure to the tests above. Specifically, we assess the relationship between our accounting variables in period *t*-2 and cash flow in period *t*; using the coefficients from the regression, we then estimate cash flow in period *t* + 2 based on accounting variables in period *t*. This procedure also is used to predict three periods ahead, and to predict the sum of cash flows for three future periods combined (*t* + 1, *t* + 2, and *t* + 3) from accounting data in period *t*. The results are given in Table 7.

For all prediction periods, *t* + 2, *t* + 3, and the three periods combined (*t* + 1, *t* + 2, and *t* + 3), the structure of the results is qualitatively similar to that in Table 3. The MAPE values for year *t* + 3 predictions are larger than those for year *t* + 2 predictions, since generally more is known in period *t* about period *t* + 2 than about period *t* + 3. However, a counter-intuitive result is that predictions for period *t* + 2 are slightly more accurate than those for period *t* +

1 in Table 3. For example, for micro companies, the MAPE in Model 1 for predicting cash flow in period $t + 1$ is 1.142 in Table 3, whereas the MAPE for predicting cash flow in period $t + 2$ is 1.066. The explanation lies in the fact that one-period-ahead predictions require fewer data points, and, therefore, the average MAPE will include companies with a shorter and riskier history. Another apparent anomaly is that the MAPE values for the three future periods combined ($t + 1$, $t + 2$, and $t + 3$) are larger than for individual periods. This result is also present in Lev et al. (2010). The reason for this is that in the case of the combined periods, the estimated coefficients need to carry information for all three periods, and this is less efficient than for just a single period.

Prediction errors in times of financial distress

A particularly important function of accounting data is to provide information when the economic circumstances of a company are below average, and especially when stakeholders may be in danger of suffering a substantial decline in the value of their investment. In these circumstances, there is greater demand for information about future cash flows. Chen et al. (2023) assess whether public companies respond to this demand. They find a positive relation between conditional conservatism and the ability of accrual components to predict future cash flows in bad news periods (defined as poor or negative cash flows). For private companies, this is an even more important issue, since there is likely to be less information in the public domain than for public companies. We address how private companies respond by evaluating their predictive accuracy when there is a high probability of financial distress.

We use the coefficients of the Zmijewski (1984) financial distress model to divide the sample into low and high probability financial distress company years since it requires relatively few financial ratios. It is well known that the relation between financial ratios and financial distress changes over time, and therefore our classification will be imperfect in view of the age of the Zmijewski sample; see for example Grice and Dugan (2001, 2003). However, although the model is not as accurate as in its original setting, the accuracy is still high. For example, Grice and Dugan (2001, Table 4, p.161) find that the classification error for new data in a later period is 75.6 percent compared with the 98.2 percent in Zmijewski (1984); more recently, Yendrawati and Adiwafi (2020, Table 7, p.78) find that the accuracy rate of the Zmijewski coefficients is 83.5 percent for a sample of Indonesian companies for the period 2014–18. Furthermore, the majority of the decline in accuracy for both samples arises from a failure to identify distressed observations, which would lead us to classify high distressed observations as low distressed. Thus, any bias in our method is against finding any distinct features in the cases of high financial distress. The results are shown in Table 8.

Table 8. Proportionate errors of forecasts for high financial distress firms.

	Model 1			Model 2		Model 3	
	MPE	MAPE	*MAPE (Table 3)*	MPE	MAPE	MPE	MAPE
High financial distress firms							
Public	0.378	0.793	*0.895*	0.390	0.589	0.425	0.522
Micro	0.634	1.277	*1.142*	0.463	1.323	0.578	1.339
Small	0.801	1.271	*1.310*	0.803	1.183	0.763	1.276
Medium	0.801	1.730	*1.856*	0.815	1.619	0.797	2.001
Large private	0.862	1.852	*1.890*	0.841	1.624	0.885	2.268

Type of firm is defined according to regulatory reporting regimes from the Companies Act 2006.

Model 1: $CFO_t = a + b.CFO_{t-1} + c.\Delta Rec_{t-1} + d.\Delta Inv_{t-1} + e.\Delta Pay_{t-1} + f.\Delta DTax_{t-1} + g.\Delta Oth_{t-1} + h.D\&A_{t-1} + j.CAP\_EXP_{t-1} + u_t$.

Model 2: $CFO_t = a + b.CFO_{t-1} + c.\{ACC_{t-1} - DA_{t-1}\} + d.CAP\_EXP_{t-1} + u_t$; DA are estimated using Kothari et al. (2005) performance-matched model $Accr_{i,t} = \alpha_0 + \alpha_1\left(\frac{1}{Assets_{i,t-1}}\right) + \alpha_2\Delta Rev_{i,t} + \alpha_3 PPE_{i,t} + \alpha_4 ROA_{i,t} + \varepsilon_{i,t}$.

Model 3: $CFO_t = a + b.CFO_{t-1} + c.CAP\_EXP_{t-1} + u_t$; where CAP_EXP_{t-1} is used as the control variable.

The prediction is constructed in two stages. The first stage is to estimate (at the prediction date, *t*) the relation between accounting numbers for period *t*−1 and the cash flow in period *t* for each industry and size group of companies. The second stage is to use the coefficients of this model to predict the cash flow in period *t* + 1, based on accounting numbers at *t* for each industry and size group of companies.

All statistics are computed after winsorizing the top 1 percentiles.

MPE is defined as the mean of proportionate error by removing scaling factor. MAPE is defined as the mean of absolute proportionate error by removing scaling factor.

Financial distress is measured using the prediction model of financial distress developed by Zmijewski (1984).

Zmijewski Score = −4.336 - [4.513 * (Net Income/Total Assets)] + [5.679 * (Total Liabilities/Total Assets)] + [0.004 * (Current Assets/Current Liabilities)]

High financial distress firms are firms with a Zmijewski score higher than 0.5.

For small, medium, and large private companies, in conditions of high financial distress, the MAPE value in Model 1 is lower than in Table 3, indicating that the predictions are more accurate in these circumstances; this finding is consistent with Chen et al. (2023). This result also holds for public companies. An important component of this increase in predictive accuracy (a lower MAPE) is accruals, since the result diminishes as total accruals are removed in Model 3. However, discretionary accruals are not informative since the prediction error falls, relative to Model 1, when they are removed in Model 2.

The increase in overall accuracy in Model 1 does not hold for micro companies; they become similar to small companies. In high financial distress conditions the MAPE for micro companies increases; for Model 1, it is 1.277 in Table 8 compared with 1.142 in Table 3. However, it seems that some informative actions are being taken by companies, since the increase is larger when accruals (both discretionary and total) are removed in Model 2 and Model 3. One reason for the relatively poor predictions in high financial distress situations is probably that the companies' activities are largely cash-based; in difficult economic circumstances, the trading of these companies is likely to be even more cash-based, as they receive and give less credit. Consequently, their accruals may be too small to carry much forward-looking information. On the positive side, the forecasts for micro companies are more accurate than those for medium and large companies, in high financial distress environments.

Summary and conclusions

The prediction of future cash flow is an important aspect of financial reporting. This attribute is commonplace when standard setters discuss the objectives of reporting. Although there is considerable literature on predictability for public companies, the work on private companies is sparse. This omission is important. Private companies in the UK have followed less stringent standards than public companies for a long time. Furthermore, this UK strategy is now endorsed by the European Union and aimed at reducing the reporting costs imposed on private companies. Nevertheless, there is little, if any, systematic evidence following these concessions to private companies about whether the reporting requirements serve the needs of stakeholders. In this paper, we contribute to this issue and examine the predictability of UK private company cash flow over the period 2006–2022. The predictions are measured against those of public companies, using the same prediction variables in order to capture more accurately the effect of the less demanding reporting standards.

Our approach is distinctive in two ways. First, we focus directly on prediction using the standard model employed in public company studies. This means we use out-of-sample tests to fully represent the position of a stakeholder making a forecast. Our summary measure of predictability is the mean absolute proportionate error (MAPE) so the absolute value of the error is scaled by the realization of future cash flow. We do not use the raw prediction error (the realization less the prediction) since both variables are scaled by lagged assets. Private companies have smaller assets than public companies at the same level of earnings, and therefore the raw prediction error contains a bias in comparing private and public companies; it tends to exaggerate the error for private companies.

A second important aspect of our study is that we conduct a separate analysis for each group of private companies (micro, small, medium and large). This reflects the wide variety of private companies and the fact that each group has its own set of financial reporting regulations. Our analysis contrasts with previous work on the predictive power of private company reporting, which aggregates all private companies together.

Our research is based on approximately 1½ million private company observations over the 2006–2022 period. The broad conclusions of our work are as follows. For micro companies, their overall MAPE is larger than that for public companies (by about 30 percent) but is lower than for other classes of private company. The reduction of the reporting burden on micro companies seems not to have had any significant undesirable consequences. For small companies, the MAPE is slightly above that for micros, but it is probably tolerable for stakeholders considering the expense of financial reporting costs. The standard deviations of MAPE among micro and small companies follow a similar pattern; hence the average values of MAPE are representative of the vast majority of companies. Medium sized and large private companies have a MAPE which is more than double that of public companies; this is also true of the standard deviation of MAPE values which indicates that there is considerable variation within the group. Given that these are substantial companies with extensive stakeholder interests, the quality of reporting may need to be reviewed, particularly for the outlying companies.

We also investigate the role played by discretionary and total accruals. When discretionary accruals are removed from the prediction process, the prediction error (MAPE) is smaller for all classes of companies. This finding suggests that discretionary accruals appear not to have information content about next period's cash flow, although this may reflect a poor separation of discretionary and nondiscretionary accruals. When all accruals are removed from the prediction process, the MAPE for micro, medium, and large private companies increases, suggesting that total accruals contain some predictive information. Small private companies are different in that their MAPE decreases slightly. However, the effect is minor, and the ranking of private companies remains the same.

In 2016 there was a major shift in reporting regulations. Two new standards were introduced for private companies (FRS 102 and FRS 105) based on the International Financial Reporting Standard for Small and Medium-sized Entities. Micro companies were now covered by a specific standard, FRS 105, instead of the FRSSE, which was an abbreviated version of regulations designed for public companies; small companies were covered by a separate section of FRS 102 instead of the FRSSE; medium-sized and large companies were covered by FRS 102 instead of standards that had applied to all UK companies, prior to the adoption of international standards by public companies in 2005.

There are two main effects of the 2016 regulation change. First, the overall MAPE for micro companies rises slightly, but they still have the smallest prediction error compared with other private companies. Second, the overall MAPE for small companies decreases, indicating that the switch from the FRSSE to the special section of FRS 102 was successful. The regime change for medium and large companies has little effect on the prediction error; in both periods, their MAPE is worryingly double that of public companies.

An important policy issue is the option for the smaller private companies to file a cutdown version of the accounts reported to shareholders. Under the recent Economic Crime and Corporate Transparency Act 2023, these options are gradually being removed. We investigate the effect of this option in the pre-2016 and post-2016 periods. In both periods, companies exercising the option have increased errors compared to those that do not. However, for small and medium-sized companies, the increase is smaller in the post-2016 period, consistent with the general regulatory policy to make the options less attractive. For micro companies, the increase is unchanged throughout the sample period, which supports the proposal to reduce the options further for these companies.

We undertake a number of supplementary tests to check the robustness of our findings. First, we undertake the Heckman adjustment for selection bias, since only those companies with sufficient data to construct predictions are included. Second, we analyze predictions for two and three periods ahead. Both tests confirm our central conclusions. Finally, we investigate the predictive quality of financial reporting in companies that have a high probability of financial distress. This is an important issue, since it is in these circumstances that informative financial reporting is at a premium. We find that small, medium-sized, and large companies have a lower forecast error when there is a high probability of distress; this is similar to public companies. The accounting numbers have greater information content. On the other hand, micro companies have a higher error in these circumstances. In addition, they no longer have the lowest prediction error of private companies; they slip into second place, with predictive power just less than small companies but still better than medium-sized and large private companies. This is, perhaps, not really surprising since these companies are largely cash-based enterprises; in difficult economic circumstances, the trading of these companies is likely to be even more cash-based, as they receive and give less credit. Consequently, their accruals may be too small to carry much forward-looking information. The downside of our analysis is that we have only six years of data since the major shift in reporting regulations in 2016. Hence, further work is necessary to establish whether these, and our other findings, are long term. Other further work relates to whether the relatively high forecast errors for medium-sized and large private companies can be reduced by regulation, for example, by future uncertainty being captured early in the financial statements.

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Data availability statement

Data is available upon request.

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Appendix. Definitions of groups of private firms

Type of firm is defined according to regulatory reporting regimes from the Companies Act 2006.

A micro-entity must meet at least two of the following conditions:

(1) turnover must be not more than £632,000
(2) the balance sheet total must be not more than £316,000
(3) the average number of employees must be not more than 10

Pre-2016:

A small company must meet at least two of the following conditions:

(1) turnover of not more than £6.5 million,
(2) a balance sheet total of not more than £3.26 million and
(3) not more than 50 employees.

A medium-sized company must meet at least two of the following conditions:

(1) a turnover of not more than £25.9 million,
(2) a balance sheet total of not more than £12.9 million and
(3) not more than 250 employees.

Post-2016:

A small company must meet at least two of the following conditions:

(1) annual turnover must be not more than £10.2 million
(2) the balance sheet total must be not more than £5.1 million
(3) the average number of employees must be not more than 50

A medium-sized company must meet at least two of the following conditions:

(1) the annual turnover must be no more than £36 million
(2) the balance sheet total must be no more than £18 million
(3) the average number of employees must be no more than 250

Large private companies are private companies that are bigger than medium-sized companies in both pre-2016 and post-2016 periods.