Adjusting for earnings volatility in earnings forecast models
Abstract

Previous research provides evidence for the negative relation between earnings volatility and earnings forecasting. This paper examines if earnings forecast models can adjust for firms’ earnings volatility and improves the forecasts by choosing a specific estimation method and a specific forecast model. The sample is divided into quartiles based on the firms’ earnings volatility, to examine if the choice of estimation method, the full sample (FS) or the first quartile (Q1) method, and the choice of forecast model, the ones by Hou et al. (2012) and Clubb and Wu (2014), matter depending on the firms’ degree of earnings volatility. The forecasts on US firms are compared based on bias and accuracy over the period 2000-2010. The results confirm the negative relation between earnings volatility and earnings forecasting. Furthermore, the choice of estimation method proves to be a way to account for earnings volatility, where the FS method shows to give better forecasts for the highest volatility firms while the Q1 method is to prefer for the lower volatility firms. The choice of model appears to not depend on earnings volatility except for the model by Clubb and Wu (2014) that works better for the lower volatility firms when using the Q1 method.

Keywords: earnings volatility, earnings forecast model, cross-sectional model, forecasting, earnings prediction
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1. Introduction

Earnings forecasts are crucial for empirical research in valuation (Li and Mohanram, 2013). Models estimating among others marginal tax rates (Blouin et al., 2010; Graham, 1996) and implied cost of capital (Hou et al., 2012; Lee et al., 2011) include earnings forecasts. The quality of the forecasts of future earnings has a big impact on how successful an investor is. Using analysts’ forecasts of earnings is most common and has for the past several years increasingly been used (Call et al., 2013). Previous research show that analysts’ earnings forecasts are in general too optimistic (Butler and Lang, 1991; O’Brien, 1988). Brown (1997) looks at analysts’ forecasts over ten years and finds an average error of 91.6 percent. The optimistic analysts’ forecasts lead to biased results that create incentives to find a better way to forecast future earnings.

While historically the prominent alternative to analysts’ forecasts has been time series forecast models, recent research in cross-sectional forecast models emerges as a viable option (Gerakos and Gramacy, 2013). Time series forecasts use collected data over time while the cross-sectional forecasts use data from a specific point in time. The result by Hou et al. (2012), showing a cross-sectional model outperforming analysts’ earnings forecasts, is the cause of an increase in popularity for cross-sectional models and particularly that model by Hou et al. (2012). This model is used in recent research, especially for implied cost of capital estimations (Jones and Tuzel, 2013; Lee et al., 2011; Patatoukas, 2012). The popularity opens up for further research in developing these kinds of models.

Clubb and Wu (2014) continue research in this field and develop another cross-sectional model for estimating future earnings. The two models by Hou et al. (2012) and Clubb and Wu (2014) rely on different accounting variables. However, both these models ignore the proven negative relation between earnings volatility and earnings forecasts (Dichev and Tang, 2009; Petrovic et al., 2009). Research on how earnings volatility affects earnings forecasts shows that the quality of earnings forecasts decreases when earnings volatility increases (Su, 2013; Tan and Sidhu, 2012). Previous researchers find that adjusting for earnings volatility by including it as an independent variable in forecast models, which neither the models by Hou et al.
(2012) and Clubb and Wu (2014) do, improves the forecasts (Minton et al., 2002; Petrovic et al., 2009).

Even though Clubb and Wu (2014) do not account for earnings volatility in their model, they account for earnings volatility by using different estimation methods, which are the methods to calculate the parameters in the forecast models. Clubb and Wu (2014) refer to the method used by Hou et al. (2012) as the full sample method (FS) and test that method on UK firms against the new method that accounts for earnings volatility, the quartile 1 method (Q1). For the model by Clubb and Wu (2014), the Q1 method has superior forecasts compared to the FS method for the lower earnings volatility firms but for the highest volatility firms the FS method is better (Clubb and Wu, 2014).

Clubb and Wu (2014) provide compelling evidence that estimation methods can be used to account for earnings volatility. However, this result is limited to the model by Clubb and Wu (2014) and their examination of UK firms and therefore more research is needed in this area. By examining the FS and the Q1 method on another market, the US market, and also on another model, the model by Hou et al. (2012), this can give indications that the choice of estimation method in general can be a way for cross-sectional models to account for earnings volatility and therefore improve forecasts. In addition, the different forecast models by Hou et al. (2012) and Clubb and Wu (2014) are examined to see if the models perform differently well depending on the degree of earnings volatility. If the models perform differently well at different degrees of earnings volatility it can be an indication that the choice of model can be another way to adjust for earnings volatility. Due to future earnings being such a big part of several areas of research, finding the combination of method and model that gives the best estimation of future earnings is of great importance. Therefore this study aims to answer the questions: Do the choice of estimation method and the choice of forecast model matter depending on firms’ degree of earnings volatility? Which combination of forecast model and estimation method gives the best forecast of future earnings?

This study is organized as follows. Section two describes the connection between earnings volatility and earnings forecasts and introduces the two earnings forecast models where the estimation methods are described in detail. Section three describes
the data, the implementation of the forecast models and estimation methods and lastly the different measures that are used to compare the forecasts from the different forecast models and estimation methods. The results and the analysis are presented in section four. Section five concludes the paper.
2. Earnings volatility and earnings forecasting

When valuating firms, forecasted earnings are an important part of the valuation (Li and Mohanram, 2013). A bad estimate of future earnings will later lead to an unreliable valuation. This section examines the relation between earnings volatility and earnings forecasting which, according to Dichev and Tang (2009), is a valuable issue for research in financial accounting. The section also introduces the two models for estimating future earnings and the different estimation methods compared in this paper.

2.1 Earnings volatility

Earnings volatility is measured as the standard deviation of earnings divided by average total assets (Clubb and Wu, 2014). A survey by Graham et al. (2005) reveals that majority of managers think that less earnings volatility leads to better earnings predictability. This belief exists even though the link between earnings volatility and earnings estimation has not historically been a widely studied area and according to researchers, there is a lot more research needed (Dichev and Tang, 2009; Petrovic et al., 2009).

Previous studies do however provide evidence for a negative relation between earnings volatility and earnings forecasts (Clubb and Wu, 2014; Dichev and Tang, 2009; Petrovic et al., 2009). Su (2013) and Tan and Sidhu (2012) state that it is easier to provide a better estimation for future earnings when there are less volatile earnings. According to Dichev and Tang (2009) economic and accounting factors, such as cash flow volatility and accruals respectively, are the main drivers of earnings volatility. These both factors have a negative impact on the earnings estimation.

Petrovic et al. (2009) investigates volatility and finds that in the UK using earnings volatility as an independent variable in the forecasting models improves the forecasts for high earnings firms and Minton et al. (2002) shows that this improves forecasting mostly for low profitability firms. These results provide empirical evidence that using earnings volatility as an independent variable in the forecasting models improves the earnings estimation. In another way, Clubb and Wu (2014) manage to account for earnings volatility by using different estimation methods. However, this result is limited to their own forecast model and the UK market and therefore more research is
needed to determine if this, in general, can be another way to adjust for earnings volatility.

2.2 Earnings forecast models
In general, previous research utilizing implied cost of capital models in both finance and accounting, use analysts’ forecasts to estimate future earnings (Botosan and Plumlee, 2002; Botosan, 1997; Chava and Puranandam, 2010; Pástor et al., 2008). This method proves to give biased results, as analysts’ forecasts are often too optimistic (Butler and Lang, 1991; Mohanram and Gode, 2013; O’Brien, 1988). Dichev and Tang (2009) state that analysts do not include earnings volatility in their forecasts. An alternative is earnings forecast models, which has been developed as an alternative to avoid the issue with analysts’ forecasts.

The two models presented here are models by Hou, van Dijk & Zhang (HVZ) and Clubb & Wu (CW). Both models are cross-sectional regressions but include different accounting variables. The reason why the HVZ model is interesting to examine is because it is being used frequently in recent research, despite receiving criticism (Jones and Tuzel, 2013; Lee et al., 2011; Patatoukas, 2012). The CW model, on the other hand, is relatively new and untested but the researchers behind the model proves that estimation methods can be used to account for volatility (Clubb and Wu, 2014).

2.2.1 Clubb & Wu’s model (CW)
Clubb and Wu's (2014) model uses a cross-sectional regression model that includes ten years of previous data to forecast earnings (the method is fully explained in part 3.2). The CW model:

\[
E_{qt+1} = \alpha_{2q} + \alpha_{c_q} C_{qt} + \alpha_{w_q} W_{qt} + \alpha_{d_q} D_{qt} + \alpha_{o_q} O_{qt} + \epsilon_{2qt+1} \quad \text{(CW)}
\]

Where \(E_{qt+1}\) is earnings, \(C_{qt}\) is cash flows from operations after interest and tax paid, \(W_{qt}\) is working capital accruals (defined as changes in accounts receivable, inventory and accounts payable from the cash flow statements), \(D_{qt}\) depreciation and depletion expenses times -1 and \(O_{qt}\) is other accruals (calculated as \(E-(C+W+D)e\)).

Clubb and Wu (2014) divide the firms into quartiles based on earnings volatility to be able to compare the effect of earnings volatility (quartile 1 = low volatility) and test
three different variations of estimation methods. The QS method uses parameters calculated from the first quartile to be able to forecast for the firms in the first quartile. Parameters calculated from the second quartiles are used to forecast for firms in the second quartile and the same goes for the last two quartiles. The Q1 method uses parameters calculated from the first quartile to forecast for all the quartiles, in contrast to the FS method (full sample) that uses the full sample to calculate the parameters that are used to forecast all the quartiles. The Q1 and QS methods account for earnings volatility by choosing the firms included in the parameter estimation based on earning volatility. The FS method, on the other hand, does not take earnings volatility into account.

When Clubb and Wu (2014) examine the methods on the CW model, the Q1 method performs equally as well as the QS method for the three first quartiles. Both methods give a better forecast than the FS method, except for the firms with the highest earnings volatility in quartile 4 where the FS method performs the best. Even though the Q1 and the QS method forecasts equally for the lower volatility firms, the Q1 performs better for firms in quartile 4 (Clubb and Wu, 2014). However, these methods and the CW model are relatively new and therefor have not been examined critically by other researchers. That the choice of estimation method can be a way to adjust for earnings volatility is so far limited to the CW model and the UK market.

When looking at the study by Clubb and Wu (2014) for all firms (not divided into quartiles), the FS method gives a positive median bias while the Q1 gives a negative, meaning the FS method gives pessimistic forecasts while the Q1 method gives optimistic forecasts. Another finding for all firms is that the mean bias is lower when using the FS method while the median bias is lower when using the Q1 method. Furthermore, the accuracy of the forecasts reduces as the earnings volatility increases, or more precise that the accuracy is worse for firms in the higher volatility quartiles. This confirms findings from previous research (Dichev and Tang, 2009; Petrovic et al., 2009; Su, 2013; Tan and Sidhu, 2012).

Regardless which method is used, the forecasts are always better for firms in quartile 1 than for firms in quartile 4. According to Clubb and Wu (2014), this result is either because firms with lower earnings volatility have higher persistence of core earnings...
components or that transitory elements in the earnings components cause a downward bias, or both. Earnings components are the accounting variables included in the model. Transitory elements in accruals are due to accrual measurement errors (Richardson et al., 2005) and real economic events cause the transitory elements in cash flows (Clubb and Wu, 2014). Accruals’ and cash flows’ relation to earnings forecasting is researched extensively and shows a strong association (Barth and Hutton, 2004; Barth et al., 1999; Farshadfar and Monem, 2013; Nam et al., 2012; Sloan, 1996). Sloan (1996) proves that investing in firms with low accruals will result in positive abnormal stock return, which points to accruals having a negative effect on future earnings.

2.2.2 Hou, van Dijk & Zhang’s model (HVZ)

The model developed by Hou et al., (2012) is also a cross-sectional regression that includes firms’ accounting variables and uses ten years of previous data to forecast earnings. The HVZ model:

\[
E_{i,t+\tau} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 Neg_{E_{i,t}} + \alpha_6 AC_{i,t} + \varepsilon_{i,t} \quad \text{(HVZ)}
\]

Where \( E_{i,t+\tau} \) is the earnings of firm \( i \) in year \( t + \tau \), \( A_{i,t} \) is the total assets, \( D_{i,t} \) is the dividend payment, \( DD_{i,t} \) is a dummy variable where 1 denotes dividend payments and 0 otherwise, \( Neg_{E_{i,t}} \) is a dummy variable where 1 denotes negative earnings and 0 otherwise and \( AC_{i,t} \) is accruals (calculated as earnings less net cash flows from operating activities).

The forecast model relies heavily on cash flows and dividends (Li and Mohanram, 2013). Some researchers does suggest that dividends are indicators of future earnings (John and Williams, 1985; Miller and Rock, 1985). However, several researchers fail to find empirical evidence for this (Benartzi et al., 1997; Penman, 1983; Watts, 1973). Hou et al. (2012) finds that their model has worse accuracy than analysts’ forecasts but still has less bias and a better earnings response coefficient (ERC). The earnings response coefficient is the most relevant measure when it comes to the implied cost of capital models. Other research has found that adjusting the analysts’ forecasted earnings improve the results for the implied cost of capital models (Guay et al., 2011). Still, Hou et al. (2012) finds that their model is better even after adjusting the
analysts’ forecasts. Compared to analysts’ forecasts, the HVZ model gives better results for firms with high earnings volatility. However, the method used by Hou et al. (2012) in this model does not take into account earnings volatility because it uses the full sample to calculate the parameters unlike the Q1 and the QS methods by Clubb and Wu (2014) that use information from earnings volatility to estimate the parameters. Instead the estimation method used by Hou et al. (2012) in the HVZ model can be seen as the same as the FS method because it uses all firms to calculate the parameters.

Li and Mohanram (2013) criticize the HVZ model and show that it gives a weaker forecast, especially for small firms with high earnings volatility. This is compared to Residual Income model (RI) and Earnings Persistence model (EP), which are two other earning forecast models. Both RI and EP give better earnings forecast than HVZ in terms of accuracy, bias and ERC. The only exception is the ERC for large firms that have lower earnings volatility. These results are not consistent with Hou et al. (2012) own result when comparing with analysts’ forecasts. Gerakos and Gramacy (2013), provide empirical evidence that HVZ performs worse than Random Walk model (RW) which only uses the current year’s earnings to forecast the next year’s earning. Li and Mohanram (2013) confirm this result but also state that the RW is not suitable for calculating implied cost of capital. Despite all the criticism, the HVZ model has been increasingly used in research (Jones and Tuzel, 2013; Lee et al., 2011; Patatoukas, 2012).

2.3 Summary
Regardless of all the criticism, the HVZ model is being used to a larger extent. The CW model is still new and is therefore not as used as the HVZ model, which explains the lack of scrutiny it has received as of now. The researchers behind the CW model present different estimation methods that make the forecasts adjust for earnings volatility (Clubb and Wu, 2014). This is because earnings volatility and earnings predictability are negatively associated. By applying the Q1 method by Clubb and Wu (2014) on the HVZ model, there is a possibility that the forecasts for low volatility firms by the HVZ model is improved. On the other hand, it can also lead to a weaker forecast. Even though Clubb and Wu (2014) manage to prove that the choice of estimation method can adjust for earnings volatility, this is only based on their own
forecast model and on the UK market. Therefore it is interesting to find out if estimation methods can adjust for earnings volatility also for other forecasts models and in that way be used as a general method to account for earnings volatility.
3. Method
This section describes the data used in this paper, the implementation of the forecast models and how to account for earnings volatility by using different estimation methods and different forecast models. Lastly this section presents the measures used for evaluating the forecasts made by the different estimation methods and forecast models.

3.1 Data
The data used in this study are taken from firms listed on the NASDAQ, NYSE and NYSE MKT. In contrast to Clubb and Wu (2014) this paper examines firms in the US market to find out if the results for the estimation method being a way to account for earnings volatility are similar or if their result are limited to the UK market. Since the forecasts are made each year between 2000 and 2010, the needed data range from 1990-2011. Out of the original sample of 7,039 firms, financial firms, duplicates and firms with completely missing data are removed, leaving 2,818 firms. Furthermore the earnings, dividends and accruals variables for the HVZ model and earnings, operating cash flows and working capital accruals variables for the CW model are winsorized annually at the 1st and 99th percentile to account for extreme values that can otherwise give misleading results.

After that, similar to Clubb and Wu (2014), observations each year missing the needed three consecutive years of earnings data prior to the forecast year to be able to calculate the earnings volatility are removed. The final sample for the parameter calculation each forecast year is seen in panel A in table 1. As the Q1 method only uses firms from the first quartile, the final sample for the parameter calculation is smaller than for the FS method that uses all firms in the calculation. One of the advantages with the cross-sectional model is that it doesn’t need firms to survive for the whole period to be used in the sample which increases the statistical power of the model (Hou et al., 2012). This also gives a larger sample in the estimation of the parameters than in the forecast where some variables other than earnings might be missing. The numbers of forecasted firms can be seen in panel B, table 1. The difference for HVZ and CW in the numbers of forecasted firms is due to the availability of the different variables’ values. The Q1 method needs the firms included in the first quartile to be known before the parameters are calculated, which is why
the number of forecasted firms for the HVZ and the CW are the same when using the Q1 method. Because the Q1 method only uses the firms from the first quartile to calculate the parameters the sample size for the Q1 method is much smaller than for the FS method, roughly one quarter of the FS sample. Survivorship bias exists in the sample, because of constraints in Datastream, which to a large extent lack the needed data from the delisted firms.

Table 1: Number of firms and total firm-year observations each forecast-year for t+1

<table>
<thead>
<tr>
<th>Year</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Sample in the parameter estimation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firms(FS)</td>
<td>1,387</td>
<td>1,598</td>
<td>1,678</td>
<td>1,780</td>
<td>1,878</td>
<td>1,962</td>
<td>2,078</td>
<td>2,180</td>
<td>2,251</td>
<td>2,308</td>
<td>2,423</td>
</tr>
<tr>
<td>Firmyears (HVZ)</td>
<td>8,327</td>
<td>10,187</td>
<td>11,804</td>
<td>13,190</td>
<td>14,469</td>
<td>15,586</td>
<td>16,698</td>
<td>17,794</td>
<td>18,747</td>
<td>19,549</td>
<td>20,380</td>
</tr>
<tr>
<td>Firmyears (CW)</td>
<td>5,032</td>
<td>6,165</td>
<td>7,157</td>
<td>8,216</td>
<td>9,328</td>
<td>10,468</td>
<td>11,681</td>
<td>12,904</td>
<td>14,106</td>
<td>15,290</td>
<td>16,378</td>
</tr>
<tr>
<td>Panel B: Number of forecasted firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firms(Q1)</td>
<td>243</td>
<td>283</td>
<td>302</td>
<td>332</td>
<td>364</td>
<td>392</td>
<td>425</td>
<td>455</td>
<td>479</td>
<td>495</td>
<td>548</td>
</tr>
<tr>
<td>Firmyears (HVZ)</td>
<td>1,267</td>
<td>1,519</td>
<td>2,303</td>
<td>2,253</td>
<td>2,579</td>
<td>2,888</td>
<td>3,214</td>
<td>3,417</td>
<td>3,765</td>
<td>4,028</td>
<td>4,302</td>
</tr>
<tr>
<td>Firmyears (CW)</td>
<td>988</td>
<td>1,170</td>
<td>1,870</td>
<td>1,706</td>
<td>1,951</td>
<td>2,206</td>
<td>2,504</td>
<td>2,705</td>
<td>3,036</td>
<td>3,338</td>
<td>3,686</td>
</tr>
</tbody>
</table>

The first row in panel A shows the number of firms included in the parameter estimation for the FS method. The second and third row show the number of firmyear observations for the HVZ and CW model each forecast year, in other words the total number of observations with all data available. The second section shows the corresponding numbers for the Q1 method. Panel B presents the number of firms included in the forecast each year. The number of firms included is equal to the number of firms with all data for the variables in the model available at the year the forecast is made. The number of forecasted firms is the same for both models for the Q1 method seeing as the firms in the first quartile need to be known before the parameters are calculated. Because the Q1 method only uses the firms from the first quartile to calculate the parameters the sample size for the Q1 method is much smaller than for the FS method, roughly one quarter of the FS sample.

3.2. How to forecast future earnings

3.2.1 Estimating the parameters
The parameters in the models are used to forecast earnings. Ten years of previous data are needed to estimate the parameters (\(\alpha\)). The parameters are calculated by a multiple
regression. If the forecast is made in year t, to estimate earnings for t+1, data from t-1 and ten years back is used. For example, if the forecast is made in year 2010 for year 2011, the parameters are calculated using data from 2000 to 2009. One parameter calculation is made for every forecast year (Li and Mohanram, 2013).

3.2.2 Forecasting t+1
After the parameters are estimated they are put in the model together with the variables from year t to calculate the forecast. Each firm’s individual values for the variables are added into the model and then the value of earnings t+1 is calculated. The number of forecasted firms is smaller than the number of firms when calculating the parameters seeing as all variables for year t used in the model need to be available to be able to forecast earnings. While the same is needed for a firm to be used in the parameter estimation, those firms just need to have complete data available for one year of the ten used in the estimation to be included in the regression.

3.2.3 Accounting for earnings volatility
Earnings volatility has been an independent variable in recent research (Minton et al., 2002; Petrovic et al., 2009). Instead, this study follows Clubb and Wu (2014) by using different estimation methods to account for earnings volatility to test if this in general can be a way to adjust for earnings volatility in forecast models. Only the Q1 and the FS method (explained in 2.1.1) are examined because even though another method by Clubb and Wu (2014), the QS method, performs as well as Q1 on the low volatility firms, the Q1 performs better for high volatility firms. The FS method is included because it has the best results for high volatility firms and is also the same as the method used by Hou et al. (2012), which gives the fairest comparison. As the Q1 method gives the best forecasts for firms with lower earnings volatility, applying this method on the HVZ model might improve the model’s forecasts for lower volatility firms. To also find out if the forecast models perform differently well depending on earnings volatility, a simple comparison between the forecasts from the HVZ and the CW model is made.

To be able to easily examine if the choice of estimation method and the choice of forecast model matters depending on the firms’ degree of earnings volatility, this study follows Clubb and Wu (2014) and divides the firms into quartiles based on earnings volatility. Quartile 1 consists of the firms with lowest earnings volatility and
quartile 4 consists of the firms with the highest. Earnings volatility is measured as the standard deviation of earnings for the ten years prior to the forecast year and then divided by average total assets for the ten years prior to the forecast year for all firms. At least three consecutive years of earnings data are needed to be able to calculate the earnings volatility (Clubb and Wu, 2014). The HVZ model is scaled by the samples average total assets each year just as the CW model is, in order to achieve good statistical results and also to be able to compare the forecasts. Scaling the variables instead of using their total values gives more reliable t-values.

3.3 How to evaluate earnings forecasts
Seeing as this paper examines earnings forecasts, measures that focus on the future predictions are needed. Unlike the previously mentioned ERC, which looks at the past, bias and accuracy are measures that are useable when looking at future predictions. The forecasts’ bias and accuracy enable a simple comparison between the FS and the Q1 method and also between the HVZ and the CW model.

In order to examine the forecasts from the different models and the different methods the forecast bias is calculated. The forecast bias is given by the difference between actual (realized) earnings and the forecasted earnings (Hou et al., 2012). If the value is positive, the forecast is too pessimistic and if the value is negative the forecast is too optimistic. The further away from zero, the more biased the forecast is.

Forecast accuracy is the absolute value of the forecast bias which gives us the total distance between the forecasted earnings and the actual earnings (Hou et al., 2012). The value can never be negative but it should be as close to zero as possible. The closer to zero the value is, the more accurate the forecast is. While a forecast can have a good value for the bias, it can still have bad accuracy. Therefore it is important to measure both values when evaluating forecast models. Even though the data are winsorized and should not be affected by extreme value, the median of the bias and accuracy are included.
4. Results and analysis

This section begins with a look at the variables in the HVZ and the CW models and the estimations of the models. Then the results of the forecasts are presented by showing the bias and accuracy of the different models using two different estimation methods, the FS and the Q1 that differ on the information included in the parameter calculation. While the FS method includes the information from the whole sample, the Q1 method only uses information from firms in the lowest earnings volatility quartile. To be able to easier compare how well the models and the methods work at different degrees of earnings volatility the results are also divided into earnings volatility quartiles. Quartile 1 includes the firms with lowest earnings volatility and quartile 4 consists with the highest. The results are explained, analyzed and then summarized.

4.1 Descriptive statistics

Table 2 displays the descriptive statistics of the variables used in the HVZ and the CW model. All variables are scaled with average total assets. For the HVZ model in panel A all variables have a positive mean except for accruals (AC), which has a negative mean. The variables for the CW model are shown in panel B. All variables have a positive mean except for other accruals (O) and depreciation (De), which have a negative mean. The standard deviation for all variables except for total assets (A) is low which can be due to the data being winsorized.

4.2 Model estimation results

Table 3 shows the coefficient estimates from regressions on the two models with the two different methods calculated from the whole collected dataset. The HVZ model with the FS methods achieves the best R-square with 0.81, narrowly followed by the CW model with the FS method with a R-square of 0.80. The Q1 method gets a much lower R-square of 0.49 for the HVZ and 0.48 for the CW model. A possible explanation to the low R-square for the Q1 method compared to the FS method is the much smaller sample size. The FS method include all firms in the calculation while the Q1 method only uses the firms from the first quartile, that is roughly one quarter of the FS sample.
When using a significance level of 5 percent, the HVZ model has significant variables for all variables except for the intercept and the two dummy variables, DD and NegE, when using the FS method. When using the Q1 method all parameters are significant except for the assets (A). Also the dividends variable is significant, proving that dividends can explain part of future earnings which is something previous researchers has failed to find evidence for (Benartzi et al., 1997; Penman, 1983; Watts, 1973). Significant variables are variables that are more likely to be not equal to zero, in other words are variables that are likely to explain something of the variation in the dependent variable. For the CW model all variables are significant for both methods except for the intercept. The negative parameter value of accruals (AC) in the HVZ

Table 2: Descriptive statistics

Panel A: HVZ model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>0.049</td>
<td>-0.614</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.020</td>
<td>2.356</td>
<td>0.201</td>
</tr>
<tr>
<td>A</td>
<td>1.000</td>
<td>0.000</td>
<td>0.021</td>
<td>0.097</td>
<td>0.482</td>
<td>56.815</td>
<td>3.125</td>
</tr>
<tr>
<td>D</td>
<td>0.018</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
<td>1.175</td>
<td>0.081</td>
</tr>
<tr>
<td>DD</td>
<td>0.343</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.475</td>
</tr>
<tr>
<td>NegE</td>
<td>0.315</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.465</td>
</tr>
<tr>
<td>AC</td>
<td>-0.056</td>
<td>-3.934</td>
<td>-0.024</td>
<td>-0.004</td>
<td>0.000</td>
<td>1.838</td>
<td>0.206</td>
</tr>
</tbody>
</table>

Panel B: CW model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>0.049</td>
<td>-0.164</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.020</td>
<td>2.356</td>
<td>0.201</td>
</tr>
<tr>
<td>C</td>
<td>0.105</td>
<td>-0.070</td>
<td>0.000</td>
<td>0.007</td>
<td>0.044</td>
<td>3.949</td>
<td>0.363</td>
</tr>
<tr>
<td>W</td>
<td>0.006</td>
<td>-0.390</td>
<td>-0.001</td>
<td>0.001</td>
<td>0.006</td>
<td>0.449</td>
<td>0.056</td>
</tr>
<tr>
<td>De</td>
<td>-0.051</td>
<td>-7.301</td>
<td>-0.017</td>
<td>-0.003</td>
<td>-0.001</td>
<td>0.004</td>
<td>0.251</td>
</tr>
<tr>
<td>O</td>
<td>-0.119</td>
<td>-8.810</td>
<td>-0.053</td>
<td>-0.011</td>
<td>-0.002</td>
<td>1.517</td>
<td>0.459</td>
</tr>
</tbody>
</table>

Panel A of this table shows the mean, median, standard deviation and select percentiles of the accounting variables included in the HVZ model. E stands for earnings before extraordinary items, A stands for total assets, D is common dividends provided for or paid, DD is a dummy variable equal to 1 for dividend payers and 0 otherwise, NegE is a dummy variable that equal 1 if the earnings are negative and 0 otherwise, AC stands for accruals calculated as earnings before extraordinary items less net cash flow from operating activities. Panel B presents the same summary statistics but for the CW model. E stands for earnings before extraordinary items, C stands for cash flows from operations after interest and tax paid, W is working capital accrual calculated as changes in account receivables, inventory and accounts payable from the cash flow statements, De is depreciation and depletion expenses times -1, O is other accruals calculated as E-(C+W+De). All variables are divided by average total assets. The values are calculated from the full sample of 2818 firms over a period ranging from 1990-2010.

When using a significance level of 5 percent, the HVZ model has significant variables for all variables except for the intercept and the two dummy variables, DD and NegE, when using the FS method. When using the Q1 method all parameters are significant except for the assets (A). Also the dividends variable is significant, proving that dividends can explain part of future earnings which is something previous researchers has failed to find evidence for (Benartzi et al., 1997; Penman, 1983; Watts, 1973). Significant variables are variables that are more likely to be not equal to zero, in other words are variables that are likely to explain something of the variation in the dependent variable. For the CW model all variables are significant for both methods except for the intercept. The negative parameter value of accruals (AC) in the HVZ
model indicates that accruals reduce the firms’ future earnings, which is consistent with the result by Sloan (1996). However, the positive parameter value for other accruals (O) in the CW model goes against the findings by Sloan (1996). Depreciation (De) in the CW model has also a negative impact on future earnings.

Table 3: Coefficient estimates

<table>
<thead>
<tr>
<th>Method</th>
<th>Intercept</th>
<th>A</th>
<th>D</th>
<th>DD</th>
<th>E</th>
<th>NegE</th>
<th>AC</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS</td>
<td>Coef</td>
<td>0.00</td>
<td>-0.003</td>
<td>0.28</td>
<td>0.002</td>
<td>0.773</td>
<td>0.001</td>
<td>-0.220</td>
</tr>
<tr>
<td></td>
<td>t-stat</td>
<td>0.48</td>
<td>-7.39</td>
<td>24.40</td>
<td>1.33</td>
<td>155.65</td>
<td>1.18</td>
<td>-47.45</td>
</tr>
<tr>
<td>Q1</td>
<td>Coef</td>
<td>0.00</td>
<td>-0.001</td>
<td>0.082</td>
<td>0.000</td>
<td>0.661</td>
<td>0.000</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>t-stat</td>
<td>2.12</td>
<td>-1.70</td>
<td>4.82</td>
<td>7.50</td>
<td>50.95</td>
<td>-6.08</td>
<td>5.15</td>
</tr>
</tbody>
</table>

Panel A shows the coefficient estimates and the corresponding t-statistics from the HVZ model using both the FS method and the Q1 method. E stands for earnings before extraordinary items, A stand for total assets, D is common dividends provided for or paid, DD is a dummy variable equal to 1 for dividend payers and 0 otherwise, NegE is a dummy variable that equal 1 if the earnings are negative and 0 otherwise, AC stands for accruals calculated as earnings before extraordinary items less net cash flow from operating activities. Panel B presents the same methods applied on the CW model. C stands for cash flows from operations after interest and tax paid, W is working capital accrual calculated as changes in account receivables, inventory and accounts payable from the cash flow statements, De is depreciation and depletion expenses times -1, O is other accruals calculated as E-(C+W+De). All variables are divided by average total assets. The regression is based on the period 1990-2010.

4.3 Comparison of the forecasting methods
This part explains the results in table 4 for each forecasting model when using the two different estimation methods, FS and Q1. The summary answers which estimation method that gives the most reliable forecast for each forecast model and if this result differ according to earnings volatility.

4.3.1 The HVZ model – comparison between the FS and the Q1 method
For the three first quartiles, the lower volatility firms, panel A in table 4 for the HVZ model shows a lower mean bias when using the Q1 method. The FS method, on the other hand, works better for the higher volatility firms in q4. The result matches Clubb and Wu's (2014) results that the Q1 method works better for the three first
quartiles and that the FS method works best for the highest volatility quartile. Looking at the median bias, the Q1 method gives a better forecast for q1 and q2 while the FS method works better for q3 and q4 which also is an indication that Q1 method is better for lower volatility firms.

Table 4: Measures of earnings forecast models quality

<table>
<thead>
<tr>
<th>Measure</th>
<th>Quartile</th>
<th>HVZ</th>
<th>CW</th>
<th>Difference</th>
<th>HVZ</th>
<th>CW</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Bias</td>
<td>q=1</td>
<td>0.0323</td>
<td>-0.0198</td>
<td>0.0522</td>
<td>0.0020</td>
<td>0.0006</td>
<td>0.0014</td>
</tr>
<tr>
<td></td>
<td>q=2</td>
<td>0.0315</td>
<td>-0.0152</td>
<td>0.0468</td>
<td>-0.0012</td>
<td>-0.0005</td>
<td>-0.0007</td>
</tr>
<tr>
<td>Mean</td>
<td>q=3</td>
<td>0.0529</td>
<td>-0.0124</td>
<td>0.0653</td>
<td>-0.0259</td>
<td>-0.0162</td>
<td>-0.0097</td>
</tr>
<tr>
<td></td>
<td>q=4</td>
<td>-0.0229</td>
<td>0.0842</td>
<td>-0.1072</td>
<td>-0.5776</td>
<td>-0.3512</td>
<td>-0.2264</td>
</tr>
<tr>
<td>All firms</td>
<td>0.0004</td>
<td>-0.0454</td>
<td>0.0458</td>
<td>-0.1008</td>
<td>-0.0935</td>
<td>-0.0073</td>
<td></td>
</tr>
<tr>
<td></td>
<td>q=1</td>
<td>0.0151</td>
<td>-0.0349</td>
<td>0.0500</td>
<td>0.0003</td>
<td>0.0001</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>q=2</td>
<td>0.0147</td>
<td>-0.0349</td>
<td>0.0496</td>
<td>-0.0047</td>
<td>-0.0042</td>
<td>-0.0005</td>
</tr>
<tr>
<td>Median</td>
<td>q=3</td>
<td>-0.0027</td>
<td>-0.0421</td>
<td>0.0393</td>
<td>-0.0307</td>
<td>-0.0004</td>
<td>-0.0303</td>
</tr>
<tr>
<td></td>
<td>q=4</td>
<td>-0.0615</td>
<td>-0.0635</td>
<td>0.0020</td>
<td>-0.1728</td>
<td>-0.0107</td>
<td>-0.1621</td>
</tr>
<tr>
<td>All firms</td>
<td>0.0100</td>
<td>-0.0378</td>
<td>0.0478</td>
<td>-0.0107</td>
<td>-0.0089</td>
<td>-0.0019</td>
<td></td>
</tr>
<tr>
<td>Panel B: Accuracy</td>
<td>q=1</td>
<td>0.0652</td>
<td>0.0910</td>
<td>-0.0258</td>
<td>0.0296</td>
<td>0.0285</td>
<td>0.0011</td>
</tr>
<tr>
<td></td>
<td>q=2</td>
<td>0.0984</td>
<td>0.1291</td>
<td>-0.0308</td>
<td>0.0916</td>
<td>0.0894</td>
<td>0.0022</td>
</tr>
<tr>
<td>Mean</td>
<td>q=3</td>
<td>0.2483</td>
<td>0.2251</td>
<td>0.0232</td>
<td>0.2027</td>
<td>0.2034</td>
<td>-0.0007</td>
</tr>
<tr>
<td></td>
<td>q=4</td>
<td>1.1337</td>
<td>0.8521</td>
<td>0.2816</td>
<td>1.1796</td>
<td>1.3432</td>
<td>-0.1636</td>
</tr>
<tr>
<td>All firms</td>
<td>0.4596</td>
<td>0.4870</td>
<td>-0.0274</td>
<td>0.5033</td>
<td>0.4631</td>
<td>0.0402</td>
<td></td>
</tr>
<tr>
<td></td>
<td>q=1</td>
<td>0.0270</td>
<td>0.0523</td>
<td>-0.0253</td>
<td>0.0137</td>
<td>0.0121</td>
<td>0.0016</td>
</tr>
<tr>
<td></td>
<td>q=2</td>
<td>0.0435</td>
<td>0.0713</td>
<td>-0.0278</td>
<td>0.0423</td>
<td>0.0461</td>
<td>-0.0038</td>
</tr>
<tr>
<td>Median</td>
<td>q=3</td>
<td>0.0984</td>
<td>0.1105</td>
<td>-0.0121</td>
<td>0.0894</td>
<td>0.1012</td>
<td>-0.0117</td>
</tr>
<tr>
<td></td>
<td>q=4</td>
<td>0.4609</td>
<td>0.3523</td>
<td>0.1086</td>
<td>0.4285</td>
<td>0.5201</td>
<td>-0.0916</td>
</tr>
<tr>
<td>All firms</td>
<td>0.0699</td>
<td>0.0962</td>
<td>-0.0263</td>
<td>0.0681</td>
<td>0.0607</td>
<td>0.0074</td>
<td></td>
</tr>
</tbody>
</table>

Panel A shows the bias for the HVZ and the CW models using both the FS method and the Q1 method. The bias is calculated as the difference between actual earnings and the forecasted earnings. A positive value for bias means a too pessimistic forecast and a negative value implies a too optimistic forecast. Panel B presents the accuracy for the HVZ and the CW models with both methods. Accuracy is measured as the absolute value of the forecast bias. A lower value means a better forecast. The results are presented for each earnings volatility quartile with q=1 being the lowest volatility firms and q=4 being the highest. All firms shows the results calculated for all firms instead of divided into quartiles. The values are the mean of the bias and the mean of the accuracy for all the forecast years over the period 2000-2010.

The mean bias for all firms is minimal when using the FS method on the HVZ model, 0.0004 compared to -0.1008 when using the Q1 method. The difference in bias is
clearer when looking at the median bias, where the FS method result is 0.0100 and the Q1 method -0.0107. Using the FS method on all firms gives a less biased forecast. While this is said, worth noticing is that the median bias for all firms using the FS method shows a pessimistic forecast while the Q1 method gives an optimistic forecast. The same difference in the median bias is found in Clubb and Wu (2014) where the FS method gives more pessimistic forecasts and the Q1 method gives optimistic. Also, panel A shows an increasingly optimistic forecast the higher volatile earnings are seeing as the value of the mean and median biases decreases and turn negative except for q3 when using the FS method on the HVZ model.

Looking at the mean accuracy on panel B in table 4 the Q1 method works better for q1-q3, while the q4 is more accurate when using the FS method. This is not consistent when looking at the median where the Q1 method shows better accuracy for all the quartiles and not only the first three. Looking at the mean, the forecast for all firms is more accurate when using the FS method. On the other hand, the Q1 method for all firms is to prefer when looking at the median accuracy. For both methods the accuracy decreases as the earnings volatility increases, which is consistent with previous research (Dichev and Tang, 2009; Petrovic et al., 2009; Su, 2013; Tan and Sidhu, 2012) and also similar to the results found by Clubb and Wu (2014).

**4.3.2 The CW model – comparison between the FS and the Q1 method**

Looking at the mean bias for CW model, table 4 shows that the Q1 method yields lower bias than the FS method for the lower volatility firms in q1 and q2. The mean bias is closer for q3 but the FS model is slightly better and for q4 the FS method shows far lower bias than the Q1 method. Once again this proves that the Q1 method performs better than the FS method for the lower volatility quartiles while the FS outperforms the Q1 at the highest volatility quartile. One exception to this finding is that the median bias in table 4 shows that the Q1 method has lower bias for every quartile.

It is interesting to note that the Q1 method has close to zero positive mean bias for q1 and then the value of the mean bias goes increasingly negative as the earnings volatility increases, meaning that the forecast gets more optimistic as the earnings volatility gets higher. This matches the results for the HVZ model. The median bias
for the Q1 method gives the same results but not as clear. Like before there is one exception to the pattern at q3 with the Q1 method. This pattern is also seen in the median bias for the FS method, while the mean bias show a pessimistic forecast on the more volatile firms. The results for all firms show that the FS method has the lower mean bias and the Q1 method has the lower median bias which is exactly the same as what Clubb and Wu (2014) finds.

The mean accuracy showed in panel B in table 4 displays similar results as the bias. For the lower volatility firms, q1-q2 and here also including q3 the Q1 method has better accuracy. For q4, the FS method has far better accuracy than the Q1 method, with 0.8521 compared to 1.3432. The median bias shows the same results with the Q1 method having the better accuracy for q1-q3 and the FS method performs better at q4. For all firms the Q1 method shows better accuracy on both the mean and the median.

4.3.3 Summary
The empirical evidence provided in table 4 prove that using the Q1 method for the lower volatility firms gives better forecasts while the FS method is to prefer for the high volatility firms, which is in line with the previous findings by Clubb and Wu (2014). Seeing as Hou et al. (2012) use the FS method for the HVZ model it might be the reason why they find that their model works better for high volatility firms. That the Q1 method provides a better forecast for q1-q3 for both models while the FS method outperforms the Q1 method for q4, is consistent with the results by Clubb and Wu (2014) showing that estimation methods are a way to account for earnings volatility. There is also a clear pattern noticeable in table 4 where the quality in the forecast estimation decreases when the firms’ volatility increases. This pattern exist regardless of which method and which model is being used. That earning volatility has a negative impact on the forecast estimation also matches previous research which confirms previous research (Dichev and Tang, 2009; Su, 2013; Tan and Sidhu, 2012). Another pattern that can be distinguished in panel A is that the forecasts become more optimistic the higher the earnings volatility becomes disregarding a few exceptions.

4.4 Comparison of the forecasting models
This part compare the results shown in table 4 from the HVZ model and the CW model, based first on the FS method and then on the Q1 method. The summary answers how the different forecast models perform on the different degrees of
earnings volatility, showing if there are differences in the models performance depending on earnings volatility.

4.4.1 The FS method – comparison between the HVZ and the CW model
When looking at the mean bias for all firms using the FS method, the HVZ model shows a far better value than the CW. The HVZ has a value of 0.004 while the CW model has -0.0454 that indicates too optimistic forecasts. When reverting to the values for the individual quartiles however, the CW shows less biased results for q1-q3 and only for q4 is the HVZ better than the CW. The median bias, on the other hand, is better for all quartiles and for all firms for the HVZ. An interesting aspect is that the median bias for the two models when using the FS method shows that the forecasts become more optimistic when the earnings volatility increases. However, the mean bias shows that this pattern for the different forecast models moves in different direction. According to the mean bias the forecasts by HVZ become more optimistic the more volatile the earnings are, while the CW model goes in the opposite direction.

The HVZ has better accuracy both at the mean and median accuracy for all firms. When looking at the mean particularly, the HVZ performs better at the q1 and q2 while CW has better accuracy at the higher volatile quartiles q3 and q4. The results are fairly consistent at the median accuracy with the only difference being the HVZ performing better also at the q3. The CW still appears to be better for higher volatile firms when looking at the median too.

4.4.2 The Q1 method – comparison between the HVZ and the CW model
When using the Q1 method the CW outperforms the HVZ on both mean and median bias and at all the quartiles. At the lower volatility quartiles the difference, both in mean and median, is small but it increases as earnings volatility increases. At q1 the difference in mean bias is 0.0014 and at the q4 the difference is 0.2264. The CW is also better for all firms but the difference to the HVZ is small. Both models follow the same pattern with a small positive bias that moves to a larger negative bias as earnings volatility increases, which means that the forecasts turn more optimistic as the firms’ volatility increase.
When it comes to accuracy, the results in table 4 are more split. Looking at mean accuracy, the CW model barely outperforms the HVZ model for q1 and q2. For q3 the HVZ model barely outperforms the CW. It is for q4 that the results show a larger divide between the models, where the HVZ model is far better than the CW model with a difference in accuracy of 0.1636. For the median accuracy the results are similar but there the HVZ model is also better at q2. For all firms the HVZ has a sizeable better performance with the mean accuracy with the difference of 0.0402 but the HVZ is also slightly worse with the median accuracy compared to the CW.

4.4.3 Summary
Referring to the FS method the CW model shows less mean bias than the HVZ model when it comes to lower volatility firms. Looking at the accuracy the results differ and show that the HVZ model is more accurate for the lower volatility firms. For high volatility firms with the FS method the two forecast models perform differently well at the two different measures. The HVZ model has a lower bias but the CW model is more accurate for the high volatility firms in q4.

When it comes to the Q1 method, the CW model clearly outperforms the HVZ regarding bias for both low and high volatility firms. However, when looking at accuracy the CW model only performs better at lower volatility firms. For the low volatility firms it is clearer that the CW model performs better than the HVZ model. For high volatility firms however it is not as clear which model is better as the HVZ model is more accurate but the CW has less bias.

Regardless model and method, a pattern can be distinguished where the forecasts become more optimistic as the earnings volatility increases. One exception is the mean bias using the FS method with the CW model where this pattern moves in the opposite direction, meaning that the forecasts become more pessimistic as earnings volatility increases.
5. Summary and conclusions

This paper is based on previous research concerning the impact of earnings volatility on earnings forecasting. Estimations methods are examined to see if they can be used to account for earnings volatility. Furthermore earnings forecast models performance on different degrees of earnings volatility are examined too see if they perform differently well which might indicate that the choice of model can be used to account for earnings volatility. The two methods tested are the FS method and the Q1 method. The FS method includes the information from all firms to calculate the parameters in the forecasts, regardless the firms’ earnings volatility. In contrast, the Q1 method uses the information from the low volatility firms. Two cross-sectional forecasting models, the HVZ model and the CW model, are examined over the years 2000-2010 on the US market to compare how well they predict future earnings and if they perform differently depending on the degree of earnings volatility. In order to study if the estimation methods and forecast models perform differently well depending on earnings volatility, the results are presented both for all firms and for the firms divided into different quartiles based on earnings volatility. Bias and accuracy are the measurements used to compare the performance of the models and the methods.

This study provides further compelling empirical evidence to the negative relation between earnings volatility and earnings forecasting. A clear pattern can be distinguished where the quality of the forecast reduces when the earnings volatility increases. The different estimation methods works unequally well for different degrees of earnings volatility. The FS method performs better on both accuracy and bias for firms in the fourth quartile, meaning for the firms with the highest earnings volatility. On the other hand, the Q1 method gives a better forecast for both accuracy and bias for the firms in q1-q3, which are firms with lower earnings volatility. This implies that the choice of estimation method in general is a way to account for earnings volatility in earnings forecasting.

The best combination of method and model depends on the degree of earnings volatility. When using the Q1 method, that is more suitable for the lower volatility firms, it is clear that the CW model gives better forecasts. Regarding bias the CW model performs better at all earning volatility quartiles while for the accuracy the CW
model is only better than the HVZ model for lower volatility firms. The CW model can still be seen as the more suitable model for the lower volatility firms seeing as the Q1 method works better for the lower volatility firms. Interesting to point out is that the forecasts using the Q1 method become more optimistic when the earnings volatility increases. Noteworthy is that the HVZ model is improved for the low volatility firms when using the Q1 method instead of the FS method but still the CW model is preferred when forecasting low volatility firms. For the FS method, that performs best for the highest volatility firms, the better choice of model depends on the measurement. For the highest volatility firms, the HVZ model is to prefer when looking at bias while the CW model gives more accurate forecasts. According to the median bias for high volatility firms when using the FS method, the forecasts are too optimistic regardless which forecast model is used. However, when looking at the mean bias the CW model goes in the opposite direction and becomes more pessimistic as earnings volatility increases.

The CW model clearly performs better for low volatility firms than the HVZ using the Q1 method. However, overall there is not any specific difference in the performance of the forecasting models depending on earnings volatility. For low volatility firms using the FS method and for high volatility firms using both the FS and the Q1 method, there does not appear to be one model that constantly outperforms the other. Rather, the results are mixed where one model performs better at one measure and the other model performs better at another measure. Therefore there does not seem to be an indication that the choice of model can be a way to account for volatility except for low volatility firms.

In conclusion this paper confirms the negative relationship between earnings volatility and earnings forecasting. Earnings volatility affect the choice of estimation method, where the FS method shows to give better forecasts for the highest volatility firms while the Q1 method is to prefer for the lower volatility firms. The choice of model appears to not depend on earnings volatility except for the CW model that works best for the lower volatility firms when using the Q1 method. The choice of model for the highest volatility firms using the FS method is depended on the importance of bias or accuracy and also whether an optimistic or pessimistic forecast is to prefer. The HVZ model has a lower bias and it gives optimistic forecasts, while the CW model is more
accurate and the mean bias shows pessimistic forecasts while the median bias shows optimistic forecasts. When adjusting for earnings volatility in earnings forecasting it is important to make the choice of estimation method depending on the degree of earnings volatility of the firms that are being forecasted.

5.1 Future research
Future research should focus on developing more advanced methods for incorporating earnings volatility in forecasting models, especially for high earnings volatility firms that are the hardest to forecast. A comparison of estimation method and using earnings volatility as an independent variable in the model as a way to account for earnings volatility is something future researchers should consider. Seeing as this paper found that the CW model using the Q1 method performs better for firms with low earnings volatility future research should examine the variables used in the model more deeply to find out why this is the case. This could later lead to models specifically developed for high and low volatility firms and thereby account for volatility using forecast models.
References


## Appendix A

Hou, Dijk & Zhang (HDZ)

\[ E_{i,t+\tau} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 D_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \epsilon_{i,t} \]

<table>
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<tr>
<th>Variable</th>
<th>Definition</th>
<th>Datastream mnemonic</th>
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<tbody>
<tr>
<td>( E_{i,t+\tau} )</td>
<td>Earnings before extraordinary items</td>
<td>WC01551</td>
</tr>
<tr>
<td>( A_{i,t} )</td>
<td>Total assets</td>
<td>WC02999</td>
</tr>
<tr>
<td>( D_{i,t} )</td>
<td>Common dividends provided for or paid</td>
<td>WC18192</td>
</tr>
<tr>
<td>( DD_{i,t} )</td>
<td>Dummy variable that equals 1 for dividend payers and 0 otherwise</td>
<td>WC18192</td>
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<tr>
<td>( E_{i,t} )</td>
<td>Earnings before extraordinary items year t</td>
<td>WC01551</td>
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<tr>
<td>( NegE_{i,t} )</td>
<td>Dummy variable that equals 1 if earnings is negative and 0 otherwise</td>
<td>WC01551</td>
</tr>
<tr>
<td>( AC_{i,t} )</td>
<td>Accruals. Calculated using the cash-flow statement method: Earnings before extraordinary items less Net cash flows from operating activities.</td>
<td>WC01551-WC04860</td>
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</table>

Clubb & Wu (CW)

\[ E_{qt+1} = \alpha_{2q} + \alpha_{c} C_{qt} + \alpha_{w} W_{qt} + \alpha_{d} De_{qt} + \alpha_{2q} O_{qt} + \epsilon_{2qt+1} \]

<table>
<thead>
<tr>
<th>Variable</th>
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<tr>
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<td>( C_{qt} )</td>
<td>Net cash flows from operating activities</td>
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<tr>
<td>( W_{qt} )</td>
<td>Working capital accruals – changes in accounts receivable, inventory and accounts payable from the cash flow statements</td>
<td>WC02051, WC03040, WC02101</td>
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<tr>
<td>( De_{qt} )</td>
<td>Depreciation and depletion expense times -1</td>
<td>WC04049</td>
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<tr>
<td>( O_{qt} )</td>
<td>Other accruals calculated as E-(C+W+D)</td>
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