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Article

Return predictability and valuation ratios: Sector-level evidence on the Johannesburg Stock Exchange

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FINANCIAL ECONOMICS | RESEARCH ARTICLE

Return predictability and valuation ratios: sector-level evidence on the Johannesburg stock exchange

Kudakwashe Joshua Chipunza¹, Hilary Tinotenda Muguto¹*, Lorraine Muguto¹ and Paul-Francois Muzindutsi¹

Abstract: The efficient market hypothesis describes an efficient market as one in which investors cannot consistently predict stock returns because prices instantly reflect all the information flowing into the market. However, return predictability has been documented in many markets. This study tests the predictability of returns using two valuation ratios—the dividend and earnings yields—on the South African market, at both aggregated and sectoral level. Unlike most studies in South Africa, this study employs an apposite present value model, accounts for structural breaks and investigates the non-linearity of the relationship between stock returns and valuation ratios. The results show that returns are predictable at both aggregated and sectoral levels. This finding has implications for market efficiency through enhanced price discovery which, in turn, has implications for investment and portfolio management. However, it should be noted that statistical significance may not

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PUBLIC INTEREST STATEMENT

This paper investigates whether two valuation ratios - the dividend yield and the earnings yield can be used to predict returns. We use seven sector indices and the broad market index on the South African market to compute monthly returns over a period spanning 1996 to 2018. The empirical findings show that the valuation ratios can predict returns of both sector indices and the broad market index. These results are contrary to the assertion from which most traditional finance theories depart, the assertion that markets are efficient in processing information such that future price changes and returns cannot be predicted using information that is already available in the market. The findings imply that valuation ratios can be used in trading strategies by investors who seek to earn abnormal returns consistently by predicting price changes.

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translate to economic significance, so there is a need to determine the latter if one intends to use any strategy that relies on this evidence.

Subjects: Financial Asset Pricing; Price Discovery; Investment & Securities; Traditional Asset Pricing Models

Keywords: Return predictability; dividend yield; earnings yield; disaggregated data; present value model; South Africa JEL classification: G11; G12; G14; G15

1. Introduction

1.1. Background

In the efficient market hypothesis, Fama (1970) maintains that stock prices reflect all available information and are, thus, unpredictable. In this hypothesis, Fama (1970) identified three levels of efficiency. In the weak form, the lowest level of efficiency, prices only reflect the information contained in historical prices (Mittal & Thakral, 2018). Thus, fundamental and private information can be used to predict price changes. In a semi-strong form, stock prices incorporate only the publicly available information, including past price information. Only private information can be employed to predict prices to earn consistent abnormal returns. Lastly, the strong form efficient market renders stock returns unpredictable since all information is fully incorporated and reflected (Patel et al., 2017).

However, there is increasing evidence of return predictability. This evidence goes against the efficient market hypothesis, more so the evidence from markets considered to be at least semistrong form efficient such as the United States, the United Kingdom and Germany. It is thus possible that markets are adaptive in terms of efficiency (Urquhart & McGroarty, 2014). The findings also cast doubt on the validity of the present value model, which suggests that only a discounted stream of dividends can predict stock prices. The ability to predict stock market returns using various variables means that the present value model lacks the pricing efficiency in terms of processing public information (Zaremba & Czapkiewicz, 2017). So, there may be a need to use different models.

1.2. Macroeconomic variables and predictability of returns in international markets

Several studies showed that stock returns could be predicted using various macroeconomic variables. For instance, Patelis (1997) found that shifts in the monetary policy could predict US stock returns using vector autoregressions. Rapach et al. (2005) found interest rates and inflation to be significant predictors of US stock returns using predictive regressions. Diether et al. (2009) found that US stock returns were predictable based on short sale strategies. Cremers and Weinbaum (2010) showed that deviations from the put-call parity could predict US stock returns. Shamsuddin and Kim (2010) showed that equity market development indicators could predict equity returns on fifty markets using variance ratio tests.

Lou (2012) found that the flow-driven return effect of mutual funds could partially explain US stock price momentum. Gupta et al. (2014) found that economic policy and equity market uncertainty, consumer sentiment and financial stress do not explain the equity premium on the US market. Narayan and Gupta (2015), found that both positive and negative oil price changes are essential predictors of US stock returns, with negative changes relatively more important. Kostakis et al. (2015) found evidence of short-horizon predictability between 1927 and 2012 on the US market. However, the predictability almost entirely disappeared in the post–1952 period and became weaker as the predictive horizon increased.

Bekiros et al. (2016) found that economic policy and macroeconomic uncertainty indices can predict US stock returns in linear estimations. Devpura et al. (2018) found that on the US market

stock return predictability was time-varying and could be explained by shocks emanating from financial variables and market volatility. Phan et al. (2018) found that the ability of economic policy uncertainty to forecast stock returns was country- and sector-dependent through the discount rate rather than the cash flow channel in sixteen countries. Balcilar et al. (2019) found evidence of causality from the economic policy uncertainties for stock return volatility of Malaysia, and both returns and volatility for South Korea.

1.3. Macroeconomic variables and predictability of returns on the South African market

Similar studies have also been done in South Africa. For instance, using weak-form efficiency tests, Magnusson and Wydick (2002), Jefferis and Smith (2005), Simons and Laryea (2006), Smith (2008), and Zhang et al. (2012) found the returns on the South African market to be unpredictable. However, Bonga-Bonga and Makakabule (2010) found that non-linear models with macroeconomic variables can be used to predict returns. Bonga-Bonga and Mwamba (2011) found evidence of return predictability and showed that non-parametric models performed better than parametric models in return predictability. Kruger (2011), using autoregressive and regime-switching non-linear models, found evidence of linear and non-linear serial dependence in returns, albeit episodic. MacFarlane (2011), using the Johansen cointegration, Granger causality and innovation accounting tests, found weak evidence of predictability of returns based on macroeconomic variables. Gupta and Modise (2013) found that interest rates, world oil production growth and money supply could predict returns.

Van Gysen et al. (2013), using nine macroeconomic variables and non-linear models, found evidence of return predictability in South Africa. Aye et al. (2013) found evidence of structural instability and variability in the predictive ability of the twenty-three variables in different regimes. Wen et al. (2015) found that US and UK market return could predict South African stock returns pre-1996 than post-1996, possibly due to regulatory reforms in the latter period. Smith and Dyakova (2014), analysing the return predictability on eight stock markets including South Africa, found that there were successive periods of predictability and non-predictability, a finding which is consistent with the Adaptive Market Hypothesis of Lo (2004). Balcilar et al. (2015) found that stock returns. Apergis and Gupta (2017) and Olivier (2018) found that unusual weather conditions in New York and South African and US interest rates and exchange rates, respectively, could predict South African returns.

Recently, Vergos and Wanger (2019) investigated the relationship between stock markets and macroeconomic data using VECM in Sub-Saharan African markets for the period between 2008 and 2018. Their findings showed that there were co-movements among sector returns in Sub-Saharan African markets which are a violation of weak-form efficiency. In South Africa, the study showed that there is short-run causality running from the consumer goods sector to the industrials sector which suggested that a shock or innovation in the consumer goods sector influences returns in the industrial sector. Also, Vergos and Wanger (2019) found short-run causality running from gross domestic product to market capitalisation, implying that changes in the economic growth impacted stock market movement in South Africa. Moreover, Rupande et al. (2019) found that market-wide investor sentiment index of macroeconomic proxies is a significant predictor of South African returns using the Generalised Autoregressive Conditional Heteroscedasticity models over a period spanning July 2002 to June 2018

1.4. Valuation ratios and predictability of returns in international markets

There is another band of literature that shows that valuation ratios could predict stock returns. According to Lewellen (2004), these ratios can track time variation in discount rates, so their ability to predict returns is based on the risk premium information they possess that is vital to asset pricing. In this regard, various studies have been conducted to examine the predictive ability of valuation ratios. Fama and French (1988) and Hodrick (1992) showed that dividend yields could predict returns on the US stock market in short horizons. In contrast, Wu and Wang (2000) and

Lewellen (2004) evidenced that the predictive ability of dividend yield and earnings-price ratios could be extended over longer horizons, albeit time-varying.

Campbell and Yogo (2006) showed that the earnings-price ratio could predict returns at various frequencies, whereas the dividend-price ratio predicted returns only at an annual frequency. However, this prediction ability weakened in the post-1952 sample. The study also showed that, even if there are predictable components in stock returns, they may be difficult to predict using inefficient statistical tests. Ang and Bekaert (2007) found no evidence of short and long-run predictability in returns using the dividend yield and the earnings yield on the French, Germany, the UK, Japanese and the US stock markets. In contrast, Black et al. (2007) found that dividend yields could predict stock returns in the G7 markets.

Ferreira and Santa-Clara (2011) found that the dividend-price, earnings growth, and priceearnings growth ratios could predict US stock returns using the some-of-the-parts method. Pettenuzzo and Timmermann (2011) found that US stock returns were predictable using the dividend yield. However, the predictive regressions parameters were highly unstable and subject to multiple breaks. Li and Yu (2012) found that overreaction and underreaction were better predictor variables than the dividend yield, stable across subsamples and robust across all the G7 markets. Jordan et al. (2014) showed that dividend yield and earnings-price ratios could explain time-varying variation in stock returns in the US and UK, respectively.

Other studies employed disaggregated data as, per Jung and Shiller (2005), aggregate data might obscure forecasting ability of valuation ratios. Also, present value models are likely to perform better with disaggregated data. McMillan (2010) showed that the dividend yield predicts returns on ten sectoral indices in the UK. However, the predictive ability diminished in the presence of large bubbles. Alexakis et al. (2010) found that valuation ratios, asset utilisation, debt, investment and liquidity ratios could predict stock returns of 47 non-financial firms on the Athens stock market. Güloğlu et al. (2016) showed that financial leverage, dividend yield and market-to-book ratios could predict stock returns of 83 Turkish firms.

Kheradyar et al. (2011) found that dividend yield, earnings yield and book-to-market ratios could predict returns of 960 companies on the Malaysian Stock Exchange. Nargelecekenler (2011) found that the price-earnings ratio could explain the variation of stock returns in 24 sectoral indices on the Turkish market. Bannigidadmath and Narayan (2016) found that the earnings-price, dividend-price, and the book-to-market ratios could forecast sectoral returns on the Indian Stock Exchange. Markus and Sormunen (2018) findings suggested that the dividend yield, price-to-earnings, and price-to-book ratios could predict returns of stocks on the Swedish stock market. Ball et al. (2020) found that the price-earnings ratio subsumes the book-to-market ratio in predicting the cross-section of stock returns on the US market.

1.5. Valuation ratios and predictability of returns in South Africa

Gupta and Modise (2012a) found no evidence of return predictability using price-dividend and price-earnings ratios on the All-Share Index over the period 2001–2009. However, the prediction power improved when predictors, such as interest rates and term spreads, were added. In a follow-up study, Gupta and Modise (2012b) found that the dividend yield and price-earnings ratios could not predict the returns of stocks over the period from 1990 to 2010. However, interest rates, money supply and world oil production were found to be significant predictors over short horizons and the inflation rate over the medium and long horizon. After accounting for data mining, the macroeconomic and financial variables had little to no predictive power in a linear predictive regression framework.

Charteris and Strydom (2016) found that the consumption aggregate wealth ratio can predict returns in South Africa using quarterly data over the period 1990–2013. This predictive power increased when the term spread was added to the model. Pane (2016) compared linear parametric

models, non-parametric and Bayesian models on their forecasting of stock return predictability on the JSE for the period spanning 1996 to 2013. To achieve this, Pane (2016) regressed stock return data against the dividend yield, consumer price index, JIBAR, FTSE and S&P 500 returns. Employing the predicted mean square error and mean absolute error, the linear model outperformed the nonparametric model. However, the Bayesian model had better performance than the linear model.

In South Africa, there is a shortage of studies that have employed disaggregated data to investigate the predictability of returns. However, Charteris and Chipunza (2020) tested the predictability of returns using dividends in a present value model that employed a panel of 22 firms over the period between 1999 and 2018. Using Pedroni's (1999; 2004), Kao's (1999) and Westerlund's (2007) panel cointegration tests and panel dynamic ordinary least squares and panel fully modified ordinary least squares, they showed that dividends move in tandem with prices. This finding implied that, in South Africa, dividends could be employed to predict the stock returns. However, Charteris and Chipunza (2020) examined the predictive ability of dividends at the firm level and not at the sectoral level.

In the amalgam of empirical evidence on the predictability of returns in South Africa, most studies employed aggregated data in their analyses. Others, however, did not consider structural breaks at a sectoral level. Yet, Hillebrand (2005) posits that, if unaccounted for, structural breaks could have long memory and persistence effects which result in higher-order unconditional moments in financial time series. Further, Andreou and Ghysels (2009) contend that structural breaks could yield erroneous inferences owing to model misspecification. Moreover, structural breaks tend to result in model instability hence ignoring structural breaks could yield biased inferences which could harm the financial risk management and optimal asset allocation (Andreou & Ghysels, 2009; Timmermann, 2001).

Further, valuation ratios could fail to predict returns at the mean but might have forecasting ability at different parts of the return distribution (Cenesizoglu & Timmermann, 2007). Besides, it has been shown that quantile regressions have higher robustness against outliers relative to least squares regressions and relatively better consistent performance under weaker stochastic performance (Hao & Naiman, 2007). Nonetheless, this has not been investigated at a sectoral level in South Africa. To this end, this study investigates valuation ratios predictive ability using cointegration techniques accounting for structural breaks and quantile regressions at both sectoral and aggregate level in South Africa. The findings of this study may help improve price discovery as investors employ these ratios in trading strategies. Also, the findings could guide academics on the importance of structural breaks and non-linear models in modelling returns in South Africa.

2. The present value model

A present value model suggested by Campbell and Shiller (1988) is employed in this examination. They derived the dividend yield model as:

$$d_{t-1} - p_t = \sum_{j=0}^{\infty} \rho^j (h_{t+j} - \Delta d_{t+j}) - \frac{k}{1 - p}$$
(1)

$$E_t h_t = E_t r_t + c, \tag{2}$$

where $d_{t-1} - p_t$ is the log of dividend yield at the start of the period; ρ is a constant discount factor; h_{t+j} is the future stock return in j period from now; k is a constant term. E_t is an expectational operator conditional at the beginning of period t; c is a constant term. Equation (1) models the log of dividend yield as a present value of all future stock returns and dividend growth Δd_{t+j} that is discounted at a rate ρ minus the constant $\frac{k}{1-\rho}$. Campbell and Shiller (1988) imposed an additional restriction such that an observable *ex-post* discount rate r_t will satisfy the condition in Equation (2)

that there is an *ex-post* rate whereby the expectation at the beginning of each period plus a constant term is equal to the *ex-ante* stock returns in period *t*. If Equation (2) is substituted into Equation (1), it yields:

$$d_{t-1} - p_t = \sum_{j=0}^{\infty} \rho^j (h_{t+j} - \Delta d_{t+j}) - K,$$
(3)

$$D_t/P_t = r - g \tag{4}$$

where $K = (c - k)/(1 - \rho)$ represents a constant discount factor. Implicitly, the log of dividend yield is equal to an expected discounted value of all future one-period growth-adjusted discounted rates. *g* denotes a constant growth rate of dividends; D_t represents dividend per stock at time *t*; P_t symbolises the price per share at time *t*. Equation (3) implies that the current dividend yield is a function of expected future returns and growth in dividends such that a lower dividend yield predicts a lower future return or a higher future dividend growth. If the discount and dividend growth rates remain constant and the constant term, *c*, has the value of zero, then Equation (3) can be re-written as Equation (4).

To account for the predictive ability of the earnings yield, Equation (1) can be extended to model earnings yield-stock return relationship. According to the dividend models, dividend changes are related to unanticipated and permanent changes in the firm's earnings (Lintner, 1956) and firms employ dividend changes to convey earnings information unknown by the market (Miller & Rock, 1985). Thus, Wu and Wang (2000) extended Campbell and Shiller (1988) PVM by incorporating earnings yield into the model. The relationship between dividends (D_t) and earnings (Y_t) can be expressed as shown in Equation (5):

$$D_t = \Lambda Y_t$$
, or converted into its natural logarithm (5)

$$d_t = y_t + \lambda, \tag{6}$$

$$y_{t-1} - p_t = \sum_{j=0}^{\infty} \rho^j \left(h_{t+j} - \Delta y_{t+j} - \Delta \lambda \right) + \left(\frac{k}{1-\rho} - \lambda \right)$$
(7)

where λ represents the log payout ratio Λ . Substituting Equation (5) into Equation (1) yields Equation (7). If the rational expectations assumption similar to Equation (2) holds, then Equation (7) can be reformulated as follows:

$$y_{t-1} - p_t = E_t \sum_{j=0}^{\infty} \rho^j (r_{t+j} - \Delta y_{t+j} - \Delta \lambda) + Z$$
(8)

$$y_{t-1} - p_t = Z + E_t \sum_{j=0}^{\infty} \rho^j (r_{t+j} - \Delta y_{t+j})$$
(9)

where $Z = K - \lambda$ is a constant, conditional on the information at t. Equation (8) can be re-written as (9) if firms follow a constant payout ratio and this suggests that high earnings yields predict high future stock returns or lower future earnings growth, and vice versa.

3. Empirical framework

3.1. Data and sample

Monthly closing prices, dividend and earnings yields for seven sector indices namely, Basic Materials (J510), Industrials (J520), Consumer Goods (J530), Health Care (J540), Consumer

Services (J550), Telecommunication (J560) and Financials (J580), and the All-Share Index (J203), were obtained from the IRESS database from 1996:01 to 2018:12. This was necessitated by data availability and the beginning of this period coincides with the period in which major economic and regulatory reforms were instituted in South Africa (Wen et al., 2015). The nominal components were deflated by the consumer price index obtained from the South African Reserve Bank. Following Charteris and Strydom (2016), the series were converted into natural logarithm and then normalised using the z-score. The number of lags was determined by the Schwarz Bayesian information criterion (SBIC, 1978) and the order of integration was determined by the Augmented Dickey-Fuller (ADF, 1979), Zivot and Andrews (ZA, 2002) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) tests.

3.2. Structural breaks in the cointegrating relationship

To account for structural breaks, the Gregory and Hansen (GH, 1996) test, a residual-based test extended from the Engle and Granger (1987) approach, was employed. It tests the null hypothesis of no cointegration at the breakpoint. The authors formulated three models; one with a level shift, one with level shift and a trend and another with regime shift where the intercept and slope change, respectively, as:

$$Y_t = \mu_1 + \mu_2 \varphi_t + \alpha_1 D Y_t + \alpha_2 E Y_t + \mathbf{e}_t$$
(10)

$$Y_t = \mu_1 + \mu_2 \varphi_t + \beta_t + \alpha_1 D Y_t + \alpha_2 E Y_t + \mathbf{e}_t$$
(11)

$$Y_t = \mu_1 + \mu_2 \varphi_t + \alpha_1 D Y_t + \alpha_{11} \varphi_t D Y_t + \alpha_2 E Y_t + \alpha_{22} \varphi_t E Y_t + e_t$$
(12)

In Equation (10), a level shift in the cointegrating relationship is modelled as a change in the intercept μ , and the slope coefficients are held constant. μ_1 signifies the intercept before the shift and μ_2 denotes the intercept subsequent to the shift. Y is the dependent variable; DY_t denotes the real log dividend yield at time t; EY_t signifies real log earnings yield at time t; a_1 and a_2 signify the cointegrating slope coefficients before the regime shift. The parameters μ_1, a_1, μ_2 and a_2 are time-invariant; t is the time subscript and e_t is the error term. To model structural change, Gregory and Hansen (1996) introduced a dummy variable φ_t defined as: $\varphi_t = 0$ if $t \leq [n\tau]$ and $\varphi_t = 1$ if $t > [n\tau]$ where the unknown parameter $\tau \in (0, 1)$ denotes the relative timing of the change point and [] signifies integer part.

 β_t represents the coefficient of the trend term t. α_{11} and α_{22} represent the change in slope coefficients. In determining a single endogenous break date in a cointegrating relationship, these models rely on the ADF, Z_a and Z_t test types. Where the absolute values of these statistics were higher than the critical values, the null hypothesis of no cointegration with structural breaks was rejected. The breakpoint was selected based on the model that had the smallest test statistic as this suggested more significant evidence against the null hypothesis of no cointegration with structural breaks. For robustness, we estimated the long-run relationship between the sectoral returns and valuation ratios using the ARDL model accounting for structural breaks as will be explained subsequently.

3.3. Autoregressive distributed lag model in the presence of structural breaks

To test the long run and short run relationship between valuation ratios and sectoral returns, we employed the ARDL bounds test. This test determines whether there is a cointegrating relationship among the variables using an *F*-test. The ARDL approach differs from Engle and Granger (1987) and Johansen and Juselius (1990) cointegration techniques in that it tests for cointegration between variables regardless of the order of integration or mutual cointegration. Also, it enables the simultaneous estimation of the long and short-run parameters considering that the dynamic error correction model (ECM) can be derived from the conditional ARDL. Further, it reduces the

number of parameters to be estimated since the test is not based on a vector autoregression, but on a single ARDL equation (Narayan, 2005).

Using the Pesaran et al. (2001) upper and lower bound critical values, the null hypothesis of no cointegration was rejected when the calculated *F*-statistic exceeded the upper critical bound. However, there was a failure to reject the null in cases where the *F*-statistic fell below the lower bound critical values. When the test statistic fell within the upper and lower bounds, the test was considered indecisive. The ARDL model was estimated as:

$$\Delta lnR_{t} = a_{01} + b_{11}lnR_{t-i} + b_{21}lnDY_{t-1} + b_{31}lnEY_{t-1} + \sum_{i=1}^{p-1} a_{1j}\Delta lnR_{t-i} + \sum_{i=1}^{q-1} a_{2j}\Delta lnDY_{t-i} + \sum_{i=1}^{r-1} a_{3j}\Delta lnEY_{t-i} + \delta D_{Y} + \varepsilon_{t}$$
(13)

where lnR, lnDY and lnEY are the returns, dividend and earnings yields, respectively; Δ is the difference operator; D_Y is a structural break dummy which equals 0 before the breakpoint and 1 thereafter; ε_t denotes the error term. The values p, q, r are the selected number of lags for the cointegrating equations based on SBIC. If cointegration was confirmed, an error correction model (ECM) was estimated accounting for structural breaks as:

$$\Delta lnR_{t} = a_{0} + \sum_{i=1}^{p-1} a_{1i} \Delta lnR_{t-1} + \sum_{i=1}^{q-1} a_{2i} \Delta lnDY_{t-1} + \sum_{i=1}^{r-1} a_{3i} \Delta lnEY_{t-1} + \delta_{1}D_{Y} + \lambda ECT_{t-1} + \varepsilon_{t}$$
(14)

where λ is the speed of adjustment; a_{1i} ; a_{2i} ; a_{3i} are the short-run coefficients. ECT_{t-1} is the error correction term which measures the adjustment speed towards the long-run equilibrium between the sectoral returns and valuation ratios after a short run deviation from the equilibrium. That said, a larger ECT_{t-1} was interpreted as a higher speed of adjustment or convergence rate and vice versa. À priori, it was expected that the ECT_{t-1} will have a statistically significant negative sign to confirm the long-run cointegration.

After estimating the ARDL-ECM in Equation (14), several diagnostic tests were conducted. Model stability was tested for using the cumulative sum of recursive residuals (CUSUM) test of Brown et al. (1975). In this test, the null hypothesis is that coefficients in the error correction model are stable is tested and the significance of any departure from the stability is assessed at 5% significance level (Brown et al., 1975). The expectation is that the cumulative sum will be within the area of the two critical lines suggesting parameter stability or otherwise if the parameters are unstable. Also, using the residuals of the ARDL-ECM estimated in Equation (14), the Breusch-Godfrey and Durbin-Watson tests were employed to test for serial correlation to avoid biased parameter estimates.

3.4. Quantile regressions

Traditional regression methods focus on the prediction of the mean only. However, the failure of a variable to predict the mean does not necessarily mean that it cannot predict other parts of the return distribution. So, this study employed quantile regressions as they provide more detailed information regarding the return distribution, which could be paramount in portfolio designation and construction (Cenesizoglu & Timmermann, 2007). Also, quantile regressions are efficient in addressing outliers, mainly if the data exhibits non-linear distributions as indicated by skewness and leptokurtosis. Thus, inferences drawn from quantile regressions are likely to have less bias since outliers are not accounted for (Koenker & Hallock, 2001).

Further, a putative state dependence of the nexus between valuation ratios and sector return could be encapsulated by different quantiles of the conditional distribution: lower (upper) quantiles are associated with bad (good) states (Cenesizoglu & Timmermann, 2007; Ma et al., 2018). Implicitly, for instance, when a variable is statistically significant in the right tail of the return

distribution, it suggests that it has predictive power in the bull state or "upmarket" and vice versa. With that in mind, this study employed quantile regressions, introduced by Koenker and Bassett (1978), to estimate the relationship of the conditional distribution in relation to other predictor variables. The conditional quantile function of y_{t+1} at quantile τ given explanatory variable x_t is defined as follows:

 $Q_{\tau}(\mathbf{y}_{t+1}|\mathbf{x}_t) = \mathbf{c}_{\tau} + \beta_{\tau}\mathbf{x}_{\tau} + \mathbf{F}_{\in \tau+1}^{-1}(\tau)$

where F_{ε} represents the distribution of errors while c_{τ} and β_{τ} denote estimated parameters. To estimate the τ^{th} conditional quantile regression, the following regression is estimated:

$$\boldsymbol{\beta}^{\boldsymbol{\tau}} = \arg\min\sum_{t=1}^{T-1} \boldsymbol{\rho}_{\boldsymbol{\tau}}(\boldsymbol{y}_{t+1} - (\boldsymbol{c}_{\boldsymbol{\tau}} + \boldsymbol{\beta}_{\boldsymbol{\tau}} \boldsymbol{x}_t))$$

where T signifies the sample size and ρ_{τ} denotes the check function that is defined as $\rho_{\tau}(\varepsilon) = \tau \varepsilon \ge 0$ and $\rho_{\tau}(\varepsilon) = (\tau - 1)\varepsilon$ (Koenker & Bassett, 1978).

4. Results

4.1. Descriptive statistics

The descriptive statistics of the sectoral indices' returns, dividend yield and earnings yield are shown in Table 1. The consumer goods sector had the highest average return (0.61%), whereas the health sector had the lowest (-0.56%). The standard deviations of the basic materials, consumer goods, consumer services, financials, health, industrials and telecommunication sector were 7.59%, 6.57%, 6.54%, 6.00%, 14.75%, 5.80% and 8.68%, respectively. These differences suggest that certain sector-specific events influenced volatility in the return series behaviour with the highest standard deviation recorded for the health sector. The risk-return relationship for the health sector suggests high risk as the high standard deviation does not result in higher returns as per finance theory. Thus, based on the standard deviation, the health sector is the riskiest of all the seven sectors.

The average real earnings yield ranged between -2.8% and 1.9% (basic materials), -1.89% and 2.09% (consumer goods), -2.05% and 1.56% (consumer services), -2.48% and 1.92% (financials), -1.87% and 1.56% (health), -1.92% and 2.03% (industrials), and -5.10% and 1.61% (telecommunication). The financials sector had the highest average earnings yield, suggesting that it outperformed the other sectors. The sector also had low variability of the earnings yield, as shown by the lowest standard deviation, and the highest average real dividend yield of 6.54\%. The telecoms sector had the lowest average real dividend yield of -0.01%. However, it should be noted that although the financials sector had the highest dividend yield, it also recorded the highest variability in the dividend yield. This suggests a higher level of risk, but this is compensated for by the high average dividend yields.

Notably, all the data series of all the sectors are not normally distributed. Instead, they are negatively skewed except for the average real dividend yields for the basic materials, consumer goods and health sectors. Most of the data series of the examined sectors show that there were a few outliers in the data as evidenced by kurtosis values of less than 3 of normal distribution. On the other hand, the stock return series for the consumer services, financials, health and industrials sectors show evidence of fat tails as the kurtosis is greater than 3. This confirms the findings of South African studies such as Gupta and Modise (2012a), who found that stock returns tend to have the fat-tailed effect. Also, the telecoms sector's earnings yield and the dividend yield had fat tails. This suggests the presence of outliers in the data series; hence interpretation of results ought to have this caveat in mind.

Table 1.	Descriptive	statistics						
Sector	Variable	Mean	Median	σ	Kurtosis	Skewness	Min.	Max.
J510	Returns	0.0887	0.0538	7.5996	1.8401	-0.1042	-25.7352	34.6562
	EY	0.0002	0.0613	1.0018	-0.3289	-0.3064	-2.8773	1.9328
	DY	0.0001	-0.0726	1.0018	-1.0349	0.0325	-1.9694	2.4905
J530	Returns	0.6164	0.8885	6.5711	2.2233	-0.5925	-25.9125	19.5953
	EY	0.0073	0.1217	1.0039	-1.0062	-0.0832	-1.8947	2.0927
	DY	-0.0003	-0.1060	1.0070	-0.2365	0.5184	-1.8254	3.0460
J550	Returns	0.6063	1.0016	6.5402	5.6621	-1.1925	-41.7638	14.0648
	EY	0.0129	0.2814	0.9994	-0.9744	-0.4692	-2.0550	1.5694
	DY	0.0148	0.4634	0.9939	-0.6922	-0.8190	-2.0965	1.2920
J580	Returns	0.1933	0.2385	6.0025	20.9529	-2.2843	-52.2968	21.1140
	EY	0.0208	0.1325	0.9870	-0.9359	-0.2615	-2.4870	1.9215
	DY	6.5451	6.5519	1.0574	1.8490	-0.3545	0.7991	8.9606
J540	Returns	-0.5621	0.4443	14.7580	18.63036	-12.4558	-222.2209	16.7077
	EY	0.0079	0.0804	1.0044	-1.2430	-0.3067	-1.8764	1.5646
	DY	-0.0004	-0.4028	1.0072	-1.5567	0.0871	-1.7862	1.6086
J520	Returns	0.2624	0.2881	5.8082	4.4858	-0.9857	-33.9490	13.7644
	EY	0.0150	0.1046	0.9967	-1.2855	-0.1784	-1.9284	2.0335
	DY	0.0119	0.0661	1.0006	-1.1235	-0.1813	-1.9958	1.9160
J560	Returns	0.3110	0.0875	8.6842	2.8059	-0.2232	-40.6570	31.1613
	EY	0.0133	0.1718	0.9988	5.1142	-1.9103	-5.1039	1.6185
	DY	-0.0108	0.0629	1.0016	-0.8680	-0.2311	-2.4116	1.9307

EY and DY denote the real log earnings yield and real log dividend yield, respectively.

4.2. Stationarity tests

ADF test results in Table 2 show that only the dividend yield of the industrials and telecommunications were stationary in levels. The same applies to the earnings yield with the addition of basic materials. The returns were stationary in levels across all sectors. For the market index, all the variables were stationary in levels. In the Zivot and Andrews (1992) test, which performs the ADF unit root test for every possible observation and selects the structural break date that yields the minimal *t*-statistic, the null hypothesis of unit roots in levels was rejected at the 1% significance level for the return series across all sectors and aggregated market. However, like the ADF unit root test, the results varied across sectors and valuation ratios as some were I (1) while some were I (0) as shown in Table 3. From the KPSS test in Table 4, the dividend and earnings yield series were stationary in first differences in the consumer services, health, financial and telecommunications sectors. Conversely, at the aggregate level, the earnings yield was stationary in first differences. The differences in the order of integration and absence of 1(2) variables necessitated the estimation of the ARDL model to test for cointegration, as suggested by Pesaran et al. (2001).

4.3. Gregory Hansen cointegration test

Following the identification of structural breaks, the GH cointegration test was then employed. The null hypothesis was rejected at the 1% significance level for all sectors and the broad market. Hence, there was strong evidence of stability in the long-run equilibrium relationship among the variables, even in the presence of structural breaks. These results were robust with the inclusion of the intercept shift term, intercept shift and trend term and intercept shift with slope term. Interestingly, Table 5 shows that there are varying breakpoints across all sectors and the broad market, signifying the presence of structural events that uniquely affected the different sectors

Table 2. Augm	ented Dickey-Fu	ller unit root te	st		
Sector	Returns	Divider	nd Yield	Earning	gs Yield
	ADF I(0)	ADF I(0)	ADF I(1)	ADF I(0)	ADF I(1)
J510	-4.6646***	-2.7938	-5.7610***	-3.6442**	
J530	-3.9787**	-2.9512	-5.1947***	-2.5354	-5.9249***
J550	-3.9432**	-1.5986	-5.6213***	-2.2476	-4.4394***
J580	-3.4292**	-2.2483	-4.5186***	-2.5838	-5.2442***
J540	-4.2907***	-1.5425	-4.1270***	-2.4488	-5.0950***
J520	-3.7962**	-3.5275**		-3.2626**	
J560	-3.6646**	-3.4972**		-3.1779**	
J203	-4.5183***	-3.7048**		-3.1812**	

*, **, *** denotes significance at 10%, 5% and 1% levels, respectively. Critical values are based on a sample size of 276 observations allowing for the inclusion of intercept and trend and lag selection based on SBIC.

Table 3. Zivot	and Andrews un	it root test			
Sector	Returns	Dividen	nd Yield	Earning	gs Yield
	ZA I(0)	ZA I(0)	ZA I(1)	ZA I(0)	ZA I(1)
J510	-17.350***	-4.275	-16.262***	-4.825***	
J530	-8.318***	-4.517	-10.760***	-3.883	-17.447***
J550	-14.793***	-4.803	-9.751***	-4.350	-9.936***
J580	-16.559***	-4.329	15.799***	-5.027*	
J540	-17.816***	-5.867***		-3.909	-18.289***
J520	-16.291***	-4.794	-10.809***	-5.692***	
J560	-8.553***	-4.177	-16.921***	-6.300***	
J203	-17.469***	-5.152**		-4.338	-8.995***

*, **, *** denotes significance at 10%, 5% and 1%, respectively. Critical values are based on 276 observations allowing for the structural break, the inclusion of intercept and trend and lag selection based on SBIC.

and the market over the sample period. Apart from the break date heterogeneity across sectors, the identification of the structural break date was sensitive to the test statistics and inclusion of the trend and slope terms.

4.4. ARDL bounds testing approach

For robustness, a bounds test for cointegration accounting for structural breaks was conducted. The results in Table 6 from the bounds test show that the *F*-statistics were consistently higher than the upper bound critical values of 3.79 and 4.68 at 5% and 1% significance levels, respectively. Following this, the bounds test concluded that there exists a cointegrating relationship among the variables even in the presence of structural breaks which corroborated results from the GH test.

4.5. Error correction model

Considering that a long-run relationship existed in the presence of structural breaks, an ARDL-ECM that accounts for structural breakpoints as specified in Equation (14) was estimated. The results in Table 7 show that the adjustment coefficient (ECT) in all the models estimated was negative and statistically significant at the 1% level. Considering that the ECT term was close to one, it suggests that disequilibrium is quickly corrected. Turning to the long-run coefficients, the results suggest that an increase in the dividend yield results in a reduction in returns of the basic materials, industrials, and telecommunications sectors. In contrast, an increase in dividend yield could

Table 4. KPSS	stationarity te	st					
Sector	Returns	5		Dividend Yield	l	Earn	ings Yield
	KPSS I(0)	KPSS	5 I(O)	KPSS I(1)	к	PSS I(0)	KPSS I(1)
J510	0.0910***	0.1650)*		0.0743)***	
J530	0.0847***	0.1269)**		0.0898)***	
J550	0.0978***	0.4969)	0.0375***	0.4287	7	0.1041***
J580	0.0500***	0.3234	÷	0.0987***	0.2411		0.0280***
J540	0.1084***	0.2758	3	0.1070***	0.2204	ł	0.1120**
J520	0.1097***	0.1406	ĵ**		0.2152)*	0.0594***
J560	0.0832***	0.3101	L	0.0305***	0.2677	7	0.0219***
J203	0.0669***	0.0797	7***		0.278		0.0423***

*, **, *** denotes significance at the 10%, 5% and 1%, respectively. Critical values are based on a sample size of 276 observations allowing for the inclusion of intercept and trend and lag selection based on SBIC.

predict an increase in returns in the financial sector in the long run based on the positive slope coefficient, but the magnitude of the slope coefficient suggests that the predicted increase is small. Also, this study found that, in contrast to the dividend yield, an increase in the earnings yield predicted an increase in returns in the basic materials and telecommunications sector as suggested by the positive slope coefficients that were significant at the 5% level.

On the other hand, an increase in the earnings yield could predict a decline in returns in the financial sector as indicated by a negative slope coefficient which was statistically significant at the 5% level. At the aggregated level, a decline in the dividend yield in the long run predicted a decline in returns. The magnitude was relatively higher than at sectoral level, considering that the dividend yield slope coefficient was negative and significant at the 5% level. However, the earnings yield failed to predict returns at the aggregated market level in the long run since the earnings yield slope coefficient was statistically insignificant at all conventional levels. Also, the results show that the breakpoint dummy coefficient was statistically significant at the 5% level in the financials, industrials, and broad market index. This suggests that the breakpoints had a significant impact on the ARDL-ECM estimated and the presence of the long-run relationship amongst the variables could be explained by the inclusion of structural breaks in the model. However, the breakpoint did not have a significant effect on the ECM estimated for the health and consumer services sectors, suggesting that caution ought to be taken when interpreting these models.

As shown in Table 7, there was strong evidence that, after accounting for structural breaks, the dividend yield and earnings yield were able to predict returns in the short run across all sectors as the results were statistically significant at the 1% level. However, we found weak evidence that dividend yield could predict returns in for the consumer goods sector since the dividend yield slope coefficient was weakly significant at the 10% level. In fact, all slope coefficients entered with a negative sign suggesting that an increase in the dividend yield and earnings yield in the short run would predict a decline in the returns across all sectors. Similar results were found at the aggregate level where the dividend yield and earnings yield slope coefficients entered at the 1% and 5% level.

Table 5. Gregory Hans	en cointegration te	st				
J510		ADF		Zt		Za
Statistic		Breakpoint	Statistic	Breakpoint	Statistic	Breakpoint
Int. shift	-16.93***	08-Mar	-16.96***	08-Mar	-283.48***	08-Mar
Int. shift + trend	-16.95***	08-Mar	-16.98***	08-Mar	-183.80***	08-Mar
Int. shift + slope	-17.03***	08-Mar	-17.06***	08-Mar	-285.10***	08-Mar
J530		ADF		Zt		Za
Int. shift	-7.84***	15-Jul	-18.32***	03-Apr	-302.28***	03-Apr
Int. shift + trend	-8.24***	03-May	-18.56***	03-Apr	-307.08***	03-Apr
Int. shift + slope	-8.01***	03-Jun	-18.66***	03-Apr	-307.24***	03-Apr
J550		ADF		Zt		Za
Int. shift	-14.76***	03-Mar	-14.79***	03-Mar	-244.22***	03-Mar
Int. shift + trend	-14.65***	03-Feb	-14.67***	03-Feb	-242.38***	03-Feb
Int. shift + slope	-14.64***	02-Feb	-14.67***	02-Feb	-242.13***	02-Feb
J580		ADF		Zt		Za
Statistic		Breakpoint	Statistic	Breakpoint	Statistic	Breakpoint
Int. shift	-16.41***	07-Mar	-16.43***	07-Mar	-273.30*	07-Mar
Int. shift + trend	-16.43***	03-Feb	16.46***	03-Feb	-273.98*	03-Feb
Int. shift + slope	-16.30***	07-Mar	-16.33***	07-Mar	-271.58*	07-Mar
J540		ADF		Zt		Za
Statistic		Breakpoint	Statistic	Breakpoint	Statistic	Breakpoint
Int. shift	-17.24***	14-Aug	-17.28***	14-Aug	-287.32***	14-Aug
Int. shift + trend	-17.35***	14-Aug	-17.39***	14-Aug	-289.00***	14-Aug
Int. shift + slope	-17.33***	14-Aug	-17.36***	14-Aug	-288.58***	14-Aug
J520		ADF		Zt		Za
Int. shift	-15.78***	03-Mar	-15.80***	03-Mar	-261.38^{***}	03-Mar
Int. shift + trend	-15.33***	03-May	-15.38***	03-May	-1254.62***	03-May
Int. shift + slope	-15.72***	07-Mar	-15.75***	07-Mar	-261.03***	07-Mar
						(Continued)

Table 5. (Continued)						
J510		ADF		Zt		Za
Statistic		Breakpoint	Statistic	Breakpoint	Statistic	Breakpoint
J560		ADF		Zt		20
Int. shift	-7.86***	10-Oct	-15.70***	02-Sep	-260.79***	02-Sep
Int. shift + trend	-8.09***	02-Dec	-15.92***	02-Aug	-264.80***	02-Aug
Int. shift + slope	-7.97***	Nov-00	-15.98***	Mar-00	-265.73***	Mar-00
J203		ADF		Zt		Za
Int. shift	-17.10^{***}	07-Aug	-17.13^{***}	07-Aug	-283.92***	07-Aug
Int. shift + trend	-16.92***	07-Apr	-16.95***	03-Mar	-281.40***	03-Mar
Int. shift + slope	-17.21***	07-Apr	-17.24***	07-Apr	-285.64***	07-Apr
*** denotes statistical signif 276 observations.	icance at the 1%. Critical	values of the models with interce	ept shift, intercept shift and	trend, and intercept shift and s	slope are based on SBIC lag	selection and sample size of

	ection and sample :	
	oe are based on SBIC lag sel	
-	and intercept shift and slop	
	ft, intercept shift and trend,	
	s of the models with intercept sh	
	notes statistical significance at the 1%. Critical values	servations.
	den	q

Table 7.	ARDL err	or correct	ion estim	ates					
Sector	ECT	Lon	g run coeffici	ents	Short run o	oefficients	Diagn	ostics	Adj-R ²
		DY	EY	Dummy	DY	EY	BG	DW	
J510	-1.0587*	-2.5376*	2.4867**	-1.8739**	-13.2845***	-13.8344**	0.4339	1.9244	0.7886
	(-20.63)	(-3.19)	(-2.61)	(-2.07)	(-6.26)	(-5.45)			
J530	-1.1110*	-0.2689	-0.0409	-3.6137**	-3.83968*	-32.4108***	0.8219	2.0137	0.8307
	(-1.71)	(-1.43)	(-1.02)	(-2.04)	(-1.91)	(-7.40)			
J550	-1.0008*	0.3308	0.6235	0.7825	-21.5182 **	* -32.6302***	1.9881	1.8725	0.9390
	(-1.79)	(1.00)	(0.63)	(0.78)	(-12.51)	(-17.79)			
J580	-1.0211*	0.7566***	-1.4132**	-1.4132	-19.6519***	-3.16974*	** 0.1539	2.1362	0.7907
	(-1.69)	(3.14)	(-2.57)	(-2.07)	(-20.88)	(2.71)			
J540	-0.9886*	-0.0004	-0.5452	-1.1254	-9.48676*	** -33.7341***	0.8541	1.9645	0.9686
	(-1.68)	(-1.09)	(-0.78)	(-0.17)	(-5.28)	(-14.62)			
J520	-1.0958*	-1.4217***	0.1269	-1.9494*	-8.53492*	** -22.6462***	0.2691	1.9560	0.8437
	(-1.72)	(2.66)	(0.93)	(-1.79)	(-6.76)	(-12.30)			
J560	-0.9859*	-1.4265**	2.4666**	3.3986**	-13.7426***	-30.1838***	0.4165	2.0685	0.7764
	(-1.85)	(-2.19)	(1.98)	(2.08)	(-9.00)	(-6.13)			
J203	-0.9878*	-2.9223**	1.8728	-2.1937*	-24.8602***	-6.49526*	* 0.2293	2.0318	0.9037
	(-1.87)	(2.20)	(1.07)	(-1.68)	(-10.46)	(2.10)			

*, **, *** denotes statistical significance at the 10%, 5% and 1% significance levels, respectively. In parentheses () are t-statistics. The lag order selection is based on SBIC, and critical values of the test are based on the sample size of 276 observations. BG—Breusch Godfrey and DW—Durbin Watson.

Table 6. ARDL bou	unds tests for the e	xistence of a coint	egrating relationsh	ір
J510	(1, 1, 2, 0, 1, 2)	Mar-08	72.073***	Cointegration
J530	(1, 2, 1, 1, 1, 1)	Jul-15	85.031***	Cointegration
J550	(1, 1, 1, 2, 0, 0)	Feb-02	35.775***	Cointegration
J580	(1, 2, 1, 0, 0, 0)	Mar-07	129.885***	Cointegration
J540	(1, 0, 1, 1, 0, 1)	Aug-14	52.917***	Cointegration
J520	(1, 1, 1, 0, 1, 0)	May-07	140.055***	Cointegration
J560	(2, 1, 1, 0, 1, 1)	Oct-10	53.453***	Cointegration
J203	(1, 2, 1, 0, 1, 2)	Apr-07	45.814***	Cointegration
Critical Values	1% Lower	1% Upper	5% Lower	5% Upper
	3.41	4.68	2.62	3.79

*** denotes statistical significance at 1%. The lag order selection is based on SBIC, and critical values of the test are based on the sample size of 276 observations. Critical values tabulated by Pesaran et al. (2001).

Diagnostic tests on the estimated ECM failed to reject the null hypothesis of no serial correlation at all significance levels according to the Breusch-Godfrey (BG) and Durbin-Watson (DW) tests suggesting that the models were correctly specified (see Table 7). Also, after the inclusion of the breakpoints, the CUSUM lied between the upper and lower 5% boundary for all models except the telecommunications model, as shown in Figure 1. This indicates that the ECMs did not suffer from instability. However, caution ought to be taken when interpreting the telecommunications model whose CUSUM deviated beyond the 5% upper and lower boundary, suggesting that the model was unstable.

4.6. Quantile regressions

An earlier study by Campbell and Yogo (2006) contended that the use of conventional student *t*-statistic to test the null hypothesis of no predictability of stock returns might be misleading due



to the persistence of the commonly used valuation ratios such as the dividend yield and price-toearnings ratios. This is because the *t*-statistic can become non-standard when the predictor variables are persistent, which often results in over-rejection of the null hypothesis. Moreover, conventional tests of the predictability of stock returns could be invalid. That is, they reject the null too frequently when the predictor variable is persistent and its innovations are highly correlated with returns (Campbell & Yogo, 2006).

Studies by Nelson and Kim (1993), Rapach and Wohar (2006), and Kothari and Shanken (1997) also argued that using the basic *t*-statistic could be misleading as it is prone to putative size distortions. To mitigate the concerns of over-rejection of the null hypothesis associated with the conventional *t*-test, this study applied the bootstrap procedure to the *t*-statistic that corresponds to the slope coefficients in the different quantiles. Following Gupta and Modise (2012b), 1000 replications were employed to compute an empirical distribution for the *t*-statistic so that the slope coefficient would be devoid of size distortions associated with the conventional *t*-statistic.

In line with our expectations, from the comparison of the bootstrapped and those without bootstrapped standard errors, the results are very sensitive to robustness tests using bootstrapped standard errors. By drawing a comparison between Tables 8 and 9, it is evident that in the multivariate quantile regression model, there were significant differences in the slope magnitude and sizes of t-statistic. In fact, the t-statistics became smaller in magnitude after the bootstrapping method was applied, which implies that the conventional t-statistics in Table 8 cannot be relied upon.¹ Therefore, following Gupta and Modise (2012b), we only report the results of the multivariate regression model that used bootstrapped standard errors summarised in Table 9.

The results show that there were differences in the predictive ability of the valuation ratios at different quantiles across the sectors. In the basic materials sector, there is strong evidence suggesting that an increase in the dividend yields would result in a decline in returns in both bad and good market conditions given that the slope coefficients were statistically significant at the 1% level at all quantiles except at the 25th quantile. However, this was more pronounced at 75th quantile as suggested by the relatively more negative slope coefficient. In contrast, the earnings yield was only able to predict returns in the basic materials sector when the market

Figure 1. CUSUM tests.

Table 8. Multiv	variate quantile	regressions with	earnings yield a	nd dividend yiel	d as regressand:	s (without boots	trapped standar	d errors)	
Sector	Reg.	25 th qu	uantile	50 th qı	Jantile	75 th qu	antile	95 th qu	ıantile
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
J510	DY	-18.5478***	-6.55	-20.1817***	-6.55	-27.1487***	-6.98	-24.0179***	-3.22
			[0000]		[0.000]		[0:000]		[0.001]
			(3.303306)		(3.081805)		(3.890377)		(7.465179)
	EY	-10.7624***	-3.34	-11.4979***	-3.34	-3.0465	-0.70	-0.9797	-0.12
			[0.004]		[0.001]		[0.484]		[0.906]
			(3.68765)		(3.440377)		(4.343028)		(8.333762)
J530	DY	-11.5071***	-5.42	-0.8569***	-11.78432	-10.9777***	-4.96	-8.0941	-1.08
			[0:000]		[0.000]		[0000]		[0.283
			(2.12389)		(1.813505)		(2.21419)		(7.517733)
	EY	-25.0242***	-5.44	-0.5058***	-21.25499	-21.1727***	-4.41	-19.5955	-1.20
			[0000]		[0.000]		[0000]		[0.230]
			(4.603851)		(3.931045)		(4.799591)		(16.29582)
J550	DY	-9.7666	-1.16	-11.2462	-1.48	-20.5075*	-1.71	-20.7571**	-2.26
			[0.246]		[0.139]		[0.089]		[0.025]
			(8.403364)		(7.574644)		(12.02043)		(9.185113)
	EY	-40.1672***	-3.75	-36.3198***	-6.12	-31.4462***	-2.83	-26.6727*	-2.64
			[0000]		[0.000]		[0.005]		[60:0]
			(10.71146)		(5.929818)		(11.11858)		(10.10567)
J580	DY	-13.7293**	-2.24	-10.7303	-1.61	-8.1813	-1.22	-3.1485	-0.56
			[0.026]		[0.108]		[0.222]		[0.573]
			(6.140912)		(6.663396)		(6.685719)		(5.575706)
	EY	-5.9752	-0.88	-10.4689	-1.53	-12.7698*	-1.73	-14.9776***	-2.76
			[0.379]		[0.127]		[0.084]		[0.006]
			(6.783733)		(6.846172)		(7.371848)		(5.421938)
									(Continued)

Table 8. (Cont	inued)								
Sector	Reg.	25 th qı	antile	50 th qı	uantile	75 th q	uantile	95 th գւ	uantile
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
J540	DY	-7.2762	-1.03	-7.5096	-1.61	-11.2804***	-2.01	-18.5910**	-2.00
			[0.302]		[0.109]		[0.012]		[0.047]
			(7.040022)		(4.667882)		(5.62405)		(9.29899)
	EY	-35.5745***	-4.11	-32.9996***	-5.69	-24.6126***	-3.49	-30.1926***	-4.88
			[0000]		[0.000]		[0.000]		[0:000]
			(8.646307)		(5.794948)		(7.058395)		(6.1882593)
J520	DY	-10.0933***	-3.75	-5.1815*	1.79	-2.8714	-0.97	-4.4798	-0.58
			[0.000]		[0.075]		[0.334]		[0.560]
			(1.2.693717)		(2.897033)		(2.967401)		(7.671563)
	EY	-18.0740***	-5.26	-25.5851***	-6.93	-26.4657***	-7.00	-17.8977*	-1.83
			[0.000]		[0.000]		[0.000]		[0.068]
			(3.433517)		(3.692671)		(3.782366)		(9.778474)
J560	DY	-18.3005***	-5.50	-13.8738***	-6.24	-14.3185***	-4.51	-10.0391	-0.98
			[0.000]		[0.000]		[0.000]		[0.328]
			(3.32993)		(2.224634)		(3.174483)		(10.25142)
	EY	-2.0516	-0.72	-6.6452***	3.49	-9.7706***	-3.59	-4.14464	-0.47
			[0.472]		[0.001]		[0.000]		[0.637]
			(2.85158)		(1.905062)		(2.718463)		(8.778786)
J203	DY	-20.7334***	-3.89	-20.4285***	-5.10	-25.7195***	-6.18	-16.0902	0.82
			[0000]		[0.000]		[000:0]		[0.410]
			(5.324934)		(4.004283)		(4.164412)		(19.51631)
	EY	-5.7340	-0.80	-7.6414	-1.42	-3.9782	-0.71	-16.0560	0.61
			[0.425]		[0.158]		[0.479]		[0.542]
			(7.172546)	_	(5.393664)		(5.609353)		(26.28796)

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Table 9. Multiv	variate quantile	regressions with	earnings yield o	nd dividend yiel	d as regressand	ds (with bootstra	pped standard	errors)	
Sector	Reg.	25 th qu	ıantile	50 th qu	ıantile	75 th qu	ıantile	95 th qu	antile
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
J510	DY	-15.38789***	-2.58	-19.59721***	-3.88	-22.88913***	-5.40	-11.973664^{***}	-3.12
			[900.0]		[0000]		[0.000]		[0:000]
			(5.970601)	1	(5.428771)		(4.236432)		(3.837713)
	EY	-7.509189**	-2.46	-7.198456**	-2.15	-2.509189	-0.41	-0.798456	-0.10
			[0.015]	1	[0.027]		[0.115]		[0.927]
			(3.056561)	1	(3.199314)		(6.056561)		(8.199314)
J530	DY	-7.104032***	-2.89	-0.731028	-0.59	-8.884281**	-2.42	-4.334478*	-0.66
			[0.004]		[0.275]		[0.016]		[0.631]
			(2.459639)	1	(1.247846)		(3.674758)		(6.567391)
	EY	-18.50263***	-3.17	-0.65273	-0.09	-19.42869**	-2.25	-18.76358	-1.08
			[0.000]		[0.978]		[0.025]		[0.402]
			(5.828159)		(7.252556)		(8.635084)		(17.383523)
J550	DY	-6.646865	-0.92	-8.336336	-1.23	-13.23075*	-1.13	-19.09349*	-1.90
			[0.287]		[0.175]		[0.192]		[0.058]
			(7.224853)		(6.777509)		(10.756707)		(10.02839)
	EY	-26.705661**	-2.21	-21.39702***	-4.35	-27.44629**	-2.20	-22.67275*	-1.92
			[0.016]		[0:000]		[0.038]		[0.064]
			(12.061946)		(4.922263)		(12.474148)		(11.74631)
J580	DY	-7.714904**	-2.18	-6.76885	-1.28	-6.39443	-1.15	-1.467841	-0.22
			[0.03]		[0.143]		[0.291]		[0.824]
			(3.538947)		(5.292853)		(5.565010)		(6.602215)
	EY	-4.565684*	-1.83	-5.892299	-0.83	-8.96655*	-1.79	-13.80229**	-2.06
			[0.073]		[0.406]		[0.093]		[0.042]
			(2.490313)		(7.08066)		(5.014523)		(6.563554)
									(Continued)

Table 9. (Conti	inued)								
Sector	Reg.	25 th qı	Jantile	50 th qu	ıantile	75 th qu	antile	95 th q	antile
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
J540	DY	-7.298712	-0.93	-6.341751	-1.52	-10.12431^{**}	-1.94	-13.894414*	-1.88
			[0.265]	<u>.</u>	[0.158]		[0.037]		[0.072]
			(7.84808)	<u>.</u>	(4.172204)		(5.218765)		(7.390646)
	EY	-24.67914***	-2.65	-26.92175***	-3.27	-17.72355***	-3.11	-21.32119***	-3.84
			[0.002]	<u>.</u>	[0000]		[0.000]		[0:000]
			(9.312883)	·	(8.23295)	1	(3.448088)		(5.552393)
J520	DY	-9.589963**	-2.64	-4.562886*	-1.69	-1.23204	-0.83	-3.477928	-0.43
			[0.014]		[0.087]		[0.542]		[0.213]
			(3.632562)	·	(2.699933)	1	(1.48439)		(8.088205)
	EY	-16.17244^{***}	-2.87	-19.15093^{***}	-3.76	-22.37833***	-3.26	-12.28367*	-1.69
			[0.000]	·	[0:000]	1	[0.000]		[0.086]
			(5.634997)		(5.093332)		(6.864518)		(7.268444)
J560	DY	-12.11507^{***}	-4.25	-11.87489^{***}	-3.65	-10.14558^{***}	-2.92	-6.897273	-0.36
			[0.000]		[0:000]		[0.004]		[0.686]
			(2.850605)		(3.253395)		(3.474515)		(19.159092)
	EY	-1.409692**	-0.43	-4.250787***	-2.78	-7.525716***	-2.76	-2.620073	-0.17
			[0.838]		[0.013]		[0.007]		[0.932]
			(3.278353)		(1.529060)		(2.718462)		(15.412194)
J203	DY	-15.04854***	-2.33	-14.22996^{***}	-4.77	-18.943215***	-4.48	-13.46974	-0.43
			[0.018]		[0:000]		[0.000]		[0.654]
			(6.458601)		(2.983220)		(4.228396)		(31.324977)
	EY	-4.085077	-0.38	-3.4182845	-1.02	-2.379966	-0.51	-10.25381	-0.25
			[0.768]		[0.472]		[0.543]		[0.910]
			(10.750203)		(3.351259)		(1.383701)		(41.015240)

was bearish as suggested by negative slope coefficients in the 25th and 50th quantiles that were statistically significant at the 5% level.

In the consumer goods sector, the dividend and earnings yield were able to predict returns at all quantiles except at the median quantile. However, the slope coefficients were significant at the 1% level only at the 25th quantile, suggesting more robust evidence for dividend yield's predictive ability for consumer goods sector in the bearish market vis-à-vis bull market. In the consumer service sector, the dividend yield did not have any predictive ability in the bearish market. However, there is evidence that an increase in the dividend yield could predict a decline in consumer service sector returns in the bullish market, albeit weak since the slope coefficients were statistically significant at the 10% level at the 75th and 95th quantiles. By contrast, a surge in earnings yield could predict a decline in returns in the sector in both bullish and bearish markets as indicated by significant negative slope coefficients.

In the financial sector, an increase in the dividend yield could predict a decline in returns only in the bear market as indicated by a negative slope coefficient at the 25th quantile. In comparison, the earnings yield exhibited predictive ability in the financial sector, and this was more pronounced in the bull market as indicated by more negative slope coefficients at the 75th and 95th quantiles. In the health sector, the dividend yield failed to predict returns in the bear market as indicated by statistically insignificant results at the 25th and median quantiles. However, in the bullish market, an increase in the dividend yield could predict a higher decline in returns as indicated by more negative slope coefficients, statistically significant at the 5% level. In contrast, an increase in earnings yield could predict a decline in health sector returns as indicated by a negative slope coefficient that was significant at the 1% level at all quantiles but became less negative at higher quantiles. Implicitly, increases in the earnings yield could predict lower declines in the health sector returns when the market is bullish vis-à-vis bearish.

In the industrial sector, an increase in dividend yield could predict a decline in returns in both market conditions as suggested by a negative slope coefficient at all quantiles except for the 75th quantile. However, at the 95th quantile, the slope coefficient was statistically insignificant at all significance levels. By contrast, there was stronger evidence that an increase in the earnings yield could predict a decline in returns in the industrial sector as indicated by slope coefficients that were significant at the 1% level at all quantiles except for the 95th quantile which was weakly significant at the 10% level. Nonetheless, this provided evidence that the earnings yield could be employed to predict returns in both bad and good market conditions. Comparatively, the earnings yield showed that it could predict a decline in returns, but this decline was more pronounced at the 50th and 75th quantile of the return distribution.

In the telecoms sector, there was strong evidence that an increase in the dividend yield predicts a decline in returns as suggested by negative slope coefficients that were statistically significant at the 1% level. Interestingly, the magnitude of the decline in returns predicted by the dividend yield declined at higher quantiles. Put differently, the magnitude of the predicted decline in returns using the dividend yield was higher in the bearish market. However, the opposite pattern is exhibited using the earnings yield as shown by a lower return decline being predicted at lower quantiles. That is, the earnings yield will predict a higher decline of returns in the bullish market relative to the bearish market. Analogous to the dividend yield, the earnings yield could not predict returns at the 95th quantile. Interestingly, at the aggregate level, the earnings yield loses its predictive power as the slope coefficients at all quantiles were statistically insignificant. In contrast, there was strong evidence that the dividend yield could predict a decline in returns in both bull and bear markets as suggested by slope coefficients that were significant at the 1% level up to the 75th quantile.

Earlier findings by Gupta and Modise (2012a; 2012b; 2013)) in South Africa suggested that the dividend yield did not have any predictive ability in both the short- and long-run at the market

level. However, our study's findings offer a refutation to this assertion; long-run and short run coefficients in the ECM were statistically significant in most models at a sectoral level, suggesting that both the earnings and dividend yields have some predictive ability in both the short- and long-run. The differences in findings can be attributed to the use of disaggregated data in our study, unlike the aggregated data in Gupta and Modise (2012a; 2012b; 2013)) studies. That is, their failure to find the predictive ability of these ratios could be attributed to the use of aggregate market data which might obscure forecasting behaviour of valuation ratios (see Jung & Shiller, 2005).

It should be noted, however, that our results at the sectoral level confirm the finding of Aye et al. (2013) that accounting for structural breaks could yield more indicative predictive behaviour of valuation ratios even though their finding was at an aggregate level. This is in line with Andreou and Ghysels (2009) argument that, if unaccounted for, structural breaks could yield erroneous inferences owing to model misspecification. Moreover, structural breaks tend to result in model instability which affects the predictability of returns; hence ignoring structural breaks could yield biased inferences (Andreou & Ghysels, 2009). Further, this finding reaffirms international studies that valuation ratios can predict returns at the sectoral level (Bannigidadmath & Narayan, 2016; McMillan, 2010). Also, our results at the aggregate level are contrary to those of Gupta and Modise (2012b) considering that the dividend yield could predict returns at different points of the return distribution. It can be reasoned that their findings were due to reliance on a linear predictive framework and ignoring the possibility that valuation ratios possess predictive power at different parts of the return distribution as argued by Cenesizoglu and Timmermann (2007).

Moreover, the study's findings confirm return predictability at a sectoral level on the South African market, as demonstrated by Vergos and Wanger (2019). They found in their study that shocks in the consumer goods sector influenced industrial sector returns. However, our study sets itself apart from Vergos and Wanger (2019) by employing valuation ratios as predictor variables of sectoral returns in South Africa. Noteworthy, their analysis was extended to the predictive ability of macroeconomic variables on aggregate stock market returns in South Africa. Albeit the predictive ability of macroeconomic variables on sectoral returns in South Africa was beyond our study's scope.

5. Conclusion

Departing from the hypothesis that markets are efficient and abnormal returns cannot be consistently earned, this study tested the ability of two valuation ratios—dividend and earnings yields —to predict returns. A present value model that incorporated the earnings yield and the dividend yield was tested in this study. This study differentiates itself from previous ones by accounting for structural breaks, making a comparison between aggregated data at broad market level and disaggregated data at the sector level and by investigating the linearity or the non-linearity of the relationship between stock returns and valuation ratios on the South African stock market.

The Gregory Hansen test provided evidence of a stable long-run equilibrium relationship among the returns, earnings yield and dividend yield in all sectors and the market, even in the presence of structural breaks. These results were confirmed by the autoregressive distributed lag model, which showed that there existed a long-run relationship between the returns and valuation ratios at both sector and broad market level after accounting for structural breaks. The subsequent error correction model showed that any disequilibrium among the variables was corrected quite speedily, providing strong evidence of the ratios' predictive ability in the short-run across all sectors and aggregate level. Also, though results vary across sectors, findings suggest that the valuation ratios could predict returns at a sectoral level across different parts of the return distribution. However, at the broad market level, earnings yield failed to predict returns at all quantile levels.

These results could be of interest to both investors and academics in numerous ways. As the information in these ratios is publicly available, the findings indicate that the South African stock market is not efficient in processing that information to be reflected in prices. The findings of this

study have implications for market efficiency as the predictability of returns will improve price discovery through the actions of investors who continually search for strategies that would enable them to earn higher returns on stock markets. Also, the findings indicated that academics ought to account for structural breaks in modelling for cointegrating relationships between valuation ratios and returns at both market and sectoral level. Further, the results suggest that the conventional present value model might be misspecified on the South African stock market since other financial variables have been shown to predict returns. From investors' perspective, in light of the quantile regression results, investors ought to consider the predictive ability of earnings yield and dividend yield across the bearish (low quantiles) and bullish (upper quantiles) market regimes.

Considering these results, this study could be extended in numerous ways. Arguably, evidence from this study could be a function of limiting itself to financial ratios. Also, findings could be subject to methodological approaches. As such, future studies could employ in-sample and out-of-sample predictive models following Bannigidadmath and Narayan (2016). Moreover, due to the influence of bubbles on asset pricing, this study could be extended by employing a present value model that is adjusted to the presence of bubbles which warrants the use of a regime-switching model that incorporates bubbles as previously done by McMillan (2010). Lastly, future studies could further disaggregate the data and assess the predictive ability of financial statement information using firm-level panel data as done by Güloğlu et al. (2016) and Alexakis et al. (2010), among others.

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Note

 The univariate estimation results were not significantly different from the multivariate estimation results. These are available upon request.

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