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ORIGINAL ARTICLE

The impact of analyst forecast errors on fundamental indexation: the Australian evidence

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Abstract

Evidence from many developed markets suggests that fundamental indices outperform capitalisation-weighted indices. Existing studies suspect a story of market mispricing, yet a mechanism has not been identified. Using Australian data, we study the relation between analyst forecast errors and the performance of various fundamental indices. We find that fundamental indices contain a relatively higher exposure to stocks with low analyst long-term growth forecasts. Valuations for these stocks are *ex ante* overly pessimistic and drive the statistical significance of alphas produced by fundamental indexation. We show how hedging against analyst forecast errors can generate additional alpha for investors using fundamental indexation.

Keywords Fundamental indexation · Smart beta · Cap-weighted index · Analyst forecast errors · French Fama alpha

JEL Classification G11 · G12

Introduction

At the end of 2021, US$1.32 trillion was invested in strategic-beta indices which are rules-based passive vehicles that reject traditional market-cap weighting methods (ETFGI 2021). The most prominent of these strategic-beta indices is based on fundamental indexation which weighs index constituents by economic fundamentals as opposed to market capitalisation. Fundamental indices (FIs) have attracted considerable attention from researchers and practitioners alike due to evidence that FIs outperform traditional market-cap weighing indices (e.g. see Arnott et al. 2005, 2013; Hsu and Campollo 2006). Previous studies have postulated that a reduced exposure to market mispricing is the source of FIs' outperformance (Arnott et al. 2005; Treynor 2005; Perold 2007).[1] However, a mechanism through which fundamental indexation reduces exposure to market mispricing has not previously been identified. Our study focuses on identifying the drivers of outperformance by investigating whether excess returns may be attributable to market mispricing as suggested by Arnott et al. (2005).

In their seminal study, Arnott et al. (2005) propose a variety of FIs using different value proxies reflecting firms' economic "footprint" including revenue, book value of equity, number of employees, dividends, and operating cash flows. The authors show that FIs based on these economic factors outperform cap-weighted indices on average by almost 2% annually. They argue that since the formation of FIs is indifferent to the market capitalisation of securities, they naturally inherit a significant lower tilt towards market errors in expectations of future growth relative to market-cap weighted indices.[2] Similarly, Treynor (2005)

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[1] Traditional market-cap weighing indices, by construction, overinvest in overvalued securities and underinvest in undervalued securities (Treynor 2005; Perold 2007). As a result, simply moving to an alternate index weighting scheme which is not correlated with market mispricing error is likely to result in an improved risk-adjusted performance. Indeed, Arnott et al. (2013) demonstrate that not only do a variety of FI strategies outperform cap-weighted indices, remarkably, the direct inverse of the same FI strategies also tend to deliver outperformance.

[2] Consider a market where half of the stocks are overvalued and the other half are undervalued. In such market, any price deviation from fair value would mechanically cause the market-cap weighting index to overweight (underweight) all currently overpriced (underpriced) stocks. Such economically significant misallocation of capital leads to

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provides a theoretic evaluation of the outperformance of FIs and concludes that FIs outperform their cap-weighted counterpart by exponentially larger amounts as market mispricing increases.[3] However, these studies do not directly test whether, and to what extent, the outperformance of FIs is driven by market errors in expectations.

Building on Mar et al. (2009), this study shows that fundamental indices in Australia outperform cap-weighted indices over an extended sample period in the Australian market. To the best of our knowledge, this study is the first to show that the outperformance of FIs is attributable to their reduced exposure to market errors in expectations. Therefore, our research contributes to the existing literature on FIs by improving the understanding of the long-term viability of fundamental indexation strategies.

A test of the degree of the exposure of FIs to market errors in expectations requires an adequate proxy of such errors. Testing the errors-in-expectations hypothesis, La Porta (1996) examines whether market expectations are too extreme using analysts' long-term growth rate (LTG) forecasts. The author finds that the average return of stocks with low LTG forecasts is 20% higher than that of stocks with high LTG forecasts and concludes that the systematic analyst forecast errors (AFE) explain significant market corrections in previously over-/under-valued securities.[4] We follow La Porta (1996) and use AFE as our proxy for the degree of *relative* exposure of FIs to market errors in expectations.[5] In light of alternative types of AFE, and for consistency with La Porta (1996), we focus on the extrapolation of past growth rates in earnings per share (EPS). We expect FIs to have a lower propensity to overweight stocks with significant positive forecast errors (i.e. overvalued stocks) relative to market-cap weighted index. We argue that the reduced exposure of FIs' to extreme market expectation errors drives their documented outperformance relative to cap-weighted indices.

Using Australian data covering the period 1993 to 2013 we find that market errors-in-expectations have varied significantly over time and that this variation is associated with significant analysts' uncertainty about the (unobservable) fair value of securities.

To examine the time series persistence of AFE, we estimate the serial correlation coefficients of AFE over a rolling 5-year window for each of the firm metrics commonly used to construct fundamental indices: Dividends (DIV), Revenue (REV), Book Value of Common Equity (BV), and Operating Cash Flows (OCF). Consistent with previous studies, we show that the serial correlation coefficients in AFE decrease monotonically over the next 1–3 years, and mean-revert completely in the fourth and fifth years of the estimation window. This suggests that an index that loads significantly on "ebullient" market long-term forecasts is more likely to experience a mean-reversion in market expectations thereafter.

We quantify the relative exposure of FIs to errors-in-expectations by analysing statistics of AFE for each of our fundamental indices relative to the market-cap weighted index. On average, the value-weighted AFE of fundamental indices are between 0.3 and 1% lower than those of the cap-weighted index. For instance, while the value-weighted median AFE estimate is about 10.3% over our sample period, this value drops to about 9.7% for our Composite Fundamental Index, equal to a 0.6% reduction in its exposure to the prospective mean reversion in long-term forecasts. Interestingly, FIs are also characterized by lower value-weighted forecast volatility, which suggests that they contain less extreme long-term forecasts relative to the cap-weighted index.

To quantify the loading of the returns of FIs on market errors-in-expectations (relative to market-cap weighted indices), we first construct a simple hedging portfolio (*HEDGEAFE*) which consists of a long position in securities with above-median analyst long-term forecasts and a short position in securities with below-median analyst long-term forecasts. We then estimate the loading of the returns of each fundamental index on this hedging portfolio, *HEDGEAFE*, by adding it as an additional factor to the Carhart (1997) four-factor model. Consistent with our prediction, the findings of the factor model indicate that fundamental indices load negatively on *HEDGEAFE*. Further, we show that the portfolio holdings of fundamental indices underweight

Footnote 2 (continued)

lower risk-adjusted performance relative to a hypothetical fair value–weighted index. If fundamental indices are capitalisation-indifferent, they are less likely to be buffeted by mispricing. The implication is that they are less afflicted by the same performance drag of cap-weighted indices.

[3] By contrast, Perold (2007) claims that fundamental indexation strategies are simply leveraging on the value premium. In his theoretical model fundamental indices do not outperform cap-weighted indices.

[4] A substantial body of literature supports the idea that long-range analyst forecasts are biased and inefficient (see, e.g. Fried and Givoly 1982; Butler and Lange 1991; Brous 1992; Brous and Kini 1993; Francis and Philbrick 1993; Kang et al. 1994; Dreman and Berry 1995; Easterwood and Nutt 1999; Abarbanell and Lehavy 2003; Richardson et al. 2004; Agrawal and Chen 2012; Bradshaw et al. 2006). However, whether investors fail to recognize analyst bias remains a contested debate (e.g. see Da and Warachka 2011; So 2013; Kothari et al. 2016 vs. Hughes et al. 2008; Baird 2020). The findings of our paper lend support to the idea that Australian investors have historically failed to recognize analyst bias which accounts for a large component of the outperformance of FIs in Australia.

[5] Financial analysts' forecasts are widely disseminated and are of substantial interest to investors and researchers (see e.g. Cragg and Malkiel 1968, Malkiel 1982, Givoly and Lakonishok 1984, and La Porta 1996).

positive errors-in-expectations by between 7 and 10% relative to a cap-weighted index which limits exposure to subsequent market corrections during the post-formation period.

Regarding the performance of fundamental indexation, we show that the documented outperformance of FIs is (1) lower after controlling for extreme *negative* errors and is (2) both economically and statistically insignificant after accounting for *positive* errors. This suggests that one of the main sources of outperformance of FIs relative to cap-weighted indices is a sizeable departure from extreme positive errors-in-expectations of the value metrics used to build these indices (e.g. *REV*, *BV*, *DIV*, and *OCF*).

We quantify the additional value-add of fundamentals-based weighting (relative to cap-weighted weighting) by re-scaling each of the FIs by the inverse of the absolute AFE. This adjustment reduces further the expectation errors contained in each fundamentals-based weighting, hence increasing the distance of FIs from cap-weighted indices. Our results show that the outperformance of FIs with AFE hedging increases the previously documented performance gap between these indices and the market-cap weighted index by between 0.5 and 1.3%, a significant performance improvement.

Hypotheses

In light of the documented links between analyst forecasts, investor expectations, and market mispricing, we propose the use of analyst forecast errors as a proxy for market mispricing. We assume these analyst forecast errors are representative of equity mispricing by all investors (*Assumption 1*). The notion that analyst forecasts are representative of market expectations (Elton et al. 1981; Fried and Givoly 1982; Vander Weide and Carleton 1988) and that analysts make systematic errors when forecasting stocks' LTG (Dechow and Sloan 1997; La Porta et al. 1997; Lakonsihok et al. 1994; Doukas et al 2002) is consistent with the literature.

We further assume that the mean reversion in analysts' LTG forecasts of EPS is evidence of analyst forecast errors (*Assumption 2*, see De Bondt and Thaler 1990; La Porta et al. 1997; Little 1962). In particular, mean reversion of analysts' EPS forecasts is a result of analysts systematically over-extrapolating the past performance of stocks. Accordingly, the (recent) past performance of a stock does not persist and performance reverts to a long-term mean, resulting in deviations from previously made forecasts.

Treynor (2005) shows that market-valuation-indifferent indexation outperforms market-cap indexation based on a reduced exposure to market mispricing. Provided that analyst forecasts are representative of market expectations and that analysts' LTG forecasts of EPS are mean-reverting, we expect lower expectation errors for fundamental indexation. The first hypothesis, H1, is:

H1 Fundamental indices exhibit systematically lower exposure to expectation errors than the cap-weighted index.

Provided *ex ante* differences between indexation strategies, we expect that excess returns of fundamental indexation can be accounted for through adjustments for analyst errors in expectations. The second hypothesis, H2, is:

H2 The excess returns of fundamental indexation can be accounted for through adjustments for analyst errors in expectations.

H2 is a corollary of H1; provided *ex ante* differences between fundamental indexation and market-cap indexation it is intuitive to expect *ex post* performance differences. H2 focuses on the question what portion of these performance differences are attributable to market mispricing caused by analyst forecast errors.

Data

Data sources

We obtain data from three different databases: Share Price and Price Relative (SPPR), International Brokers Estimate System (IBES), and Aspect Huntley (AH). SPPR provides monthly stock returns, which we use to evaluate the post-formation performance of market cap indexation and various fundamental indices. The IBES database provides data on long-term growth forecasts of company EPS and other accounting variables. We use LTG EPS data to (1) investigate analyst over-extrapolation of past returns as a source of market mispricing and (2) the portfolio formation process for fundamental indexation. From AH we obtain additional accounting data that we use in the portfolio formation process including book value, cash flow, revenue, and gross dividends.

Sample selection and summary statistics

We select the sample period of 1993 to 2013 for several reasons. First, the limited availability of IBES data pre-1993 governs the start of our period under investigation. Second, the volatile inflation climate in Australia, prior to the Reserve Bank of Australia's (RBA) introduction of inflation targets between 2 and 3 percent in 1993, suggests using LTG forecasts from the period after the monetary policy introduction.

Table 1 Summary statistics for LTG forecasts of stock EPS

	N	Median forecast (%)	Mean Forecast (%)	Lowest forecast (%)	Highest forecast (%)	Percentiles LTG forecast				Std. dev. estimate	Mean analyst estimates per observation
						5%	25%	75%	95%		
Entire sample	55,907	12.60	12.78	8.82	17.10	− 7.70	3.96	14.80	39.60	8.82	2.54
Subsamples											
1993–1997	1518	9.21	9.21	9.21	9.21	1.00	5.00	12.00	20.00	9.21	1.00
1998–2002	15,172	10.74	11.14	6.64	16.47	− 1.80	3.70	13.00	32.60	6.64	2.55
2003–2007	19,612	14.58	14.77	10.49	19.44	− 2.20	4.30	15.00	44.79	10.49	2.76
2008–2013	23,605	12.37	12.41	8.81	16.08	− 14.42	3.50	15.20	43.42	8.81	2.46

This table presents descriptive statistics of analyst long-term growth (LTG) forecasts of stock earnings per share (EPS) obtained from IBES for the 1993 to 2013 sample period. IBES records analyst LTG forecast data on a monthly basis. Four subperiods show forecast differences over time. Subsamples begin in January and end in December of the respective year.

The availability of IBES data differs substantially over the sample period, as shown in Table 1. One observation is that the availability of data substantially increases over the sample period. While the entire sample from 1993 to 2013 contains 55,907 observations, averaging 2795 per year, 5-year subperiod averages contain increasing numbers of observations over time. Over the period 1993 to 1997 our sample contains 300 observations per year, compared to an average of 4700 observations per year for the 2008 to 2013 period. Five-year subperiods show median LTG forecasts ranging from 9.21% for 1993 to 1997 to 14.58% for 2003 to 2007 with a standard deviation ranging from 6.64% for the 1998 to 2002 period to 10.49% for the 2003 to 2007 period. The 5th percentile of LTG forecasts ranges from − 14.42% in the most recent subperiod in the sample from 2008 to 2013 to 1.00% for the 1993 to 1997 period. By contrast, the 95th percentile ranges from 20.00 to 43.42% in the periods 1993 to 1997 and 2008 to 2013, respectively, indicating a widening of the relative forecast range in the sample.

Empirical analysis

LTG forecasts as proxy for market mispricing

We require a proxy for market mispricing to assess whether the excess return of fundamental indexation (relative to market-cap indexation) is attributable to an observable form of market mispricing. We use IBES' analyst 5-year growth forecasts, relative to actual growth, as an observable proxy for *ex post* market mispricing. The LTG variables examined are EPS, dividends (DIV), revenue (REV), book value (BV), and cash flows (CF).[6]

[6] We remove LTG forecasts of less than − 100% and merge the remaining data with monthly stock returns obtained from the SPPR database

Following existing studies, we assume that the views of analysts are representative of the views of market participants (Elton et al. 1981; Fried and Givoly 1982; Vander Weide and Carleton 1988). Therefore, LTG forecasts are expected to influence the present valuation of each stock. In line with De Bondt and Thaler (1990) we analyse correlation between logarithmic 5-year growth rates and actual growth for each of the LTG variables. If analysts over-extrapolate past performance in their valuations of equities, as the literature suggests (De Bondt and Thaler 1990; Dechow and Sloan 1997; Lakonsihok et al. 1994), then mean reversion in LTG growth rates will result in companies with high (low) LTG forecasts being *ex ante* overvalued (undervalued).

Table 2 shows Pearson correlation coefficients for selected accounting variables between analyst long-term growth forecasts (GR5YR) and actual growth rates.

For each variable in Table 2 we observe monotonically decreasing correlation between analysts' forecasted growth and actual growth as the length of the forecast period increases. For 1-year ahead forecasts we find that correlations between forecasted and actual growth for all variables exceed 0.86. However, extending the forecast period beyond 1 year ahead, positive correlations decrease rapidly and vanish beyond 3 years, yielding an average of 0.21 across all variables for the 3-year ahead horizon. For the forecast horizon of four and 5 years ahead, all correlations exhibit negative values. Except for the 4 years ahead horizon, all estimated correlations are statistically significant at a 99% confidence level.

The mean reversion of actual growth rates relative to analyst LTG forecasts, as shown in Table 2, suggests analyst over-extrapolation of past performance. The positive decreasing correlation of EPS growth rates for up to 3 years ahead, and negative thereafter, is consistent with the over-extrapolation hypothesis of La Porta et al. (1997). Similarly to De Bondt and Thaler (1990), we observe that analyst forecasts of changes in EPS are substantially overestimated. If analysts systematically over-extrapolate past

Table 2 Correlation between predicted growth rates of accounting variables and actual growth rates

Forecasted 5-year growth rate	N	1 year ahead	2 year ahead	3 year ahead	4 year ahead	5 year ahead
GR5YR(EPS)	29,736	0.8649***	0.5428***	0.2279***	−0.0075***	−0.0882***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GR5YR(DIV)	15,059	0.8664***	0.5271***	0.2101***	−0.0374*	−0.1324***
		(0.000)	(0.000)	(0.000)	(0.065)	(0.000)
GR5YR(REV)	11,691	0.8636***	0.5165***	0.1969***	−0.0333	−0.1445***
		(0.000)	(0.000)	(0.000)	(0.132)	(0.000)
GR5YR(BV)	10,899	0.8622***	0.5129***	0.1955***	−0.0397*	−0.1507***
		(0.000)	(0.000)	(0.000)	(0.075)	(0.000)
GR5YR(CF)	14,421	0.8659***	0.5268***	0.2108***	−0.0383*	−0.1470***
		(0.000)	(0.000)	(0.000)	(0.063)	(0.000)

This table presents the Pearson's correlation between future period growth rates and the analyst forecasted long-term growth rate for five accounting variables employed for the construction of five fundamental indices. GR5YR denotes the analyst forecasted 5-year growth rate in earnings per share (EPS), dividends (DIV), revenue (REV), book value (BV), and cash flow (CF). Logarithmic growth rates are presented for 1 to 5 years ahead forecasts. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated *p*-values in parentheses.

growth when projecting future growth, then they overestimate (underestimate) the future growth of companies with recent strong (poor) performance. Given investors' dependence on analyst forecasts, analysts' over-extrapolation of past growth likely induces significant market mispricing.

Performance of portfolios formed on LTG forecasts

Having established a link between analyst over-extrapolation of past performance, and the resulting mispricing of equities, we need to verify that contrarian strategies exhibit outperformance due to this mispricing. The performance of a portfolio comprised of above median LTG forecast firms is compared with a portfolio comprised of below median LTG forecast firms. Intuitively, above (below) median LTG firms should be *ex ante* overvalued (undervalued) and *ex post* underperform (outperform) the broader market.

We compare the performance of buy-and-hold portfolios formed on LTG forecasts. In December of each year we rank equities based on their median/mean LTG EPS analyst forecasts and construct one portfolio comprised of stocks with above median/mean forecasts (High F_LTG) and another portfolio comprised of stocks with a below median/mean forecast (Low F_LTG). Next, we construct a hedging portfolio (HML LTG) against market mispricing. The portfolio contains two equally weighted positions. The first is a long position in stocks with an above median LTG EPS forecast, and the second is a short position in stocks with a below median LTG EPS forecast, such that:

$$\sum_{i=1}^{N} \mathrm{NomInv}_i = 0 \tag{1}$$

where NomInv_i is the dollar investment in stock i and N is the total number of stocks in the given period for which analyst LTG forecast data are available. Table 3 presents a comparison of the performance of the High F_LTG, Low F_LTG, and HML LTG portfolios for median (Panel A) and mean (Panel B) LTG EPS forecasts.

We observe an economically and statistically significant underperformance of the above median/mean LTG EPS forecast portfolios. As shown in Panel A, the above median LTG portfolio underperforms the below median LTG by 7.59% p.a. in the immediate year post-formation. The underperformance of the above median LTG portfolio is consistent across post-formation years, decreasing to 4.23% in the 15 year post-formation. This underperformance is statistically significant at the 99% confidence level for all post-formation periods analysed.

The outperformance of the below median LTG portfolio relative to the above median portfolio is even more pronounced when considering volatility. The below median LTG portfolio exhibits a lower annual volatility than the above median LTG portfolio, ranging from 4.70% lower for 1 year ahead to 6.86% lower for the 5-year ahead period. Importantly, the outperformance of the below median LTG portfolio is not the result from selecting stocks with a higher market beta. The above median LTG portfolio exhibits a Capital Asset Pricing Model (CAPM) beta coefficient that ranges from 0.23 higher than the below median portfolio for 1 year ahead to 0.27 higher for 5 years ahead. The

Table 3 Post-formation returns of portfolios formed on LTG forecasts

	N	1 year ahead	2 year ahead	3 year ahead	4 year ahead	5 year ahead
Panel A: Buy-and-hold realised returns (in %) of portfolios formed on median analyst forecasts of EPS LTG						
[1] Low F_LTG	105	19.00	14.39	15.14	16.21	16.93
[2] High F_LTG	104	11.41	7.57	10.19	12.04	12.69
HML LTG (excess return [2]–[1])		−7.59***	−6.82***	−4.95***	−4.17***	−4.24***
HML LTG (excess 12-month volatility)		4.70***	5.78***	6.63***	6.66***	6.86***
HML LTG (excess CAPM β)		0.23***	0.23***	0.25***	0.27***	0.27***
Panel B: Buy-and-hold realised returns (in %) of portfolios formed on mean analyst forecasts of EPS LTG						
[1] Low F_LTG	105	18.94	14.42	15.07	16.08	16.74
[2] High F_LTG	104	11.51	7.57	10.25	12.16	12.86
HML LTG (Excess return [2]–[1])		−7.43***	−6.85***	−4.82***	−3.92**	−3.88**
HML LTG (Excess 12-month volatility)		4.44***	5.54***	6.46***	6.61***	6.77***
HML LTG (Excess CAPM β)		0.24***	0.24***	0.26***	0.27***	0.27***

This table presents the comparison of annual post-formation returns of a portfolio formed on stocks with above median analyst LTG EPS forecasts (High F_LTG) versus a portfolio formed on stocks with below median analyst LTG EPS forecasts (Low F_LTG). HML LTG indicates the excess return of High F_LTG minus Low F_LTG. Panel A refers to portfolios constructed using stocks above/below the median of *median* analyst forecasts. Panel B refers to portfolios constructed using stocks above/below the median of *mean* analyst forecasts. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively

underperformance of stocks with a higher beta is consistent with the findings of Frazzini and Pedersen (2014) who find that tracking error and investment mandate constraints induce overvaluation of high beta stocks.

In conjunction with the observed mean reversion of actual growth rates relative to analyst LTG forecasts (see Table 2), the analysis of performance differences between above and below median and mean LTG forecast portfolios as shown in Table 3 suggests that analyst over-extrapolation of past growth induces systematic market mispricing in the Australian stock market. This result has an important implication: since the HML LTG portfolio exhibits economically and statistically significant underperformance for all forecast periods analysed, a result that is magnified when considering volatility to assess risk-adjusted performance, a short position in such a portfolio may prove a suitable hedge against market mispricing.

The relation between the high-minus-low LTG portfolio and established risk premia

We have identified that a HML portfolio formed on LTG EPS forecasts generates statistically significant negative returns. To strengthen our assertion that this is a case of market mispricing, we need to rule out the possibility that the underperformance of the HML LTG portfolio is the result of high exposures to established risk premia. Therefore, we examine performance attribution of the HML LTG EPS portfolio's returns using the CAPM, Fama-French and Carhart models.

As a benchmark, we construct and track the monthly returns of a market cap-weighted index over the sample period. We employ the well-known Carhart model (Carhart 1997) to quantify the excess return of various strategies:

$$\begin{aligned}\mathrm{ExRet}_{it} = \alpha_{it} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t \\ + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{MOM}}\mathrm{MOM}_t + \varepsilon_{it}\end{aligned} \tag{2}$$

where ExRet_{it} is the observed excess return of portfolio i over the risk-free rate at time t, β_{MKT} is the estimated market risk sensitivity, β_{HML} is the estimated book-to-market factor loading, β_{SMB} is the estimated size factor loading, and β_{MOM} is the estimated 1-year momentum factor loading. For the momentum factor returns are calculated on an 11-month lagged by 1-month basis. The use of the Carhart model provides insight into whether the performance of fundamental indexation is partially attributable to specific factor tilts.

Whilst we also employ Jensen's alpha (Jensen 1968) and Fama-French regressions (Fama and French 1993), our focus is predominately on the results of the Carhart model. The Carhart model is considered to be more robust than the alternate models for the purpose of performance evaluation due to its ability to capture the effect of momentum. Panel A and Panel B in Table 4 offer summary information with complete regression results presented in Table 11 in Appendix.

As shown in Panel A, the HML LTG portfolio generates a consistently negative excess return that is statistically significant at the 99% confidence level across all regressions and all post-formation years. This important finding suggests that the underperformance of above median analyst LTG forecast stocks relative to below median analyst LTG forecast stocks is not attributable to established risk premia.

Table 4 Excess returns of HML LTG hedging portfolios and relation to established risk premia

	1 year ahead	2 year ahead	3 year ahead	4 year ahead	5 year ahead
Panel A: Alpha of HML hedging portfolios					
CAPM	−0.0780***	−0.0648***	−0.0516***	−0.0468***	−0.0468***
	(0.0204)	(0.0144)	(0.0132)	(0.0132)	(0.0120)
3 Factor	−0.0828***	−0.0708***	−0.0588***	−0.0540***	−0.0552***
	(0.0216)	(0.0156)	(0.0144)	(0.0132)	(0.0132)
4 Factor	−0.0876***	−0.0708***	−0.0576***	−0.0552***	−0.0564***
	(0.0216)	(0.0156)	(0.0144)	(0.0144)	(0.0132)
Panel B: Beta of HML hedging portfolios					
Market					
CAPM	0.2443***	0.2434***	0.2572***	0.2697***	0.2706***
	(0.0505)	(0.0329)	(0.0313)	(0.0307)	(0.0300)
3 Factor	0.2271***	0.2343***	0.2496***	0.2577***	0.2569***
	(0.0502)	(0.0334)	(0.0318)	(0.0312)	(0.0303)
4 Factor	0.2340***	0.2336***	0.2482***	0.2588***	0.2578***
	(0.0510)	(0.0341)	(0.0323)	(0.0315)	(0.0306)
SMB	0.1064***	0.0588**	0.0516**	0.0667***	0.0736***
	(0.0387)	(0.0258)	(0.0235)	(0.0222)	(0.0208)
HML	0.0302	0.0608	0.0588	0.0583	0.0664
	(0.0788)	(0.0539)	(0.0495)	(0.0470)	(0.0453)
MOM	0.0312	−0.0031	−0.0069	0.0055	0.0045
	(0.0391)	(0.0265)	(0.0241)	(0.0227)	(0.0215)

This table presents the findings of the CAPM, Fama-French, and Carhart regressions on the post-formation returns of high minus low (HML) portfolios constructed on median analyst forecasts of long-term growth rate (LTG) in earnings per share (EPS). Panel A shows the annualised alphas of HML hedging portfolios constructed on median forecasts of LTG in EPS, with standard errors in parentheses. The table shows a consistently negative alpha; across each model and in all post-formation periods. The negative alpha is statistically significant at the 99% confidence level for all estimates. The negative alpha highlights the underperformance of a HML portfolio constructed on median forecasts of LTG in EPS, indicating the portfolio's suitability as a hedging instrument against analyst forecast errors. Panel B shows the annualised factor loadings on risk premia for HML hedging portfolios formed on median forecasts of LTG in EPS. All factor loadings are presented for the Carhart model, while only factor loadings for the market risk premium are presented for the CAPM and Fama-French model. Additional related results are presented in Appendix (Table 11). Across models and varying time periods we estimate the loadings of different factor models. The moderately low positive factor loadings for systematic risk are indicative that above median LTG equities typically exhibit higher systematic risk then below median LTG equities. The small positive factor loading for SMB indicates that above median LTG portfolios on average exhibit slightly lower market capitalisations. The HML LTG portfolio does not exhibit statistically significant factor loadings for the HML or momentum risk premia, at a 90% confidence level. Standard errors are presented in parentheses below each estimate. Statistical significance at the 1% level is denoted by ***

Panel B shows that estimated market betas range from 0.23 to 0.27 for the HML LTG portfolio with all estimates being significant at a 99% confidence level. This is indicative of the higher market betas of above median LTG forecast stocks as previously discussed for Table 3. The SMB (small minus big) betas range from 0.05 to 0.11, suggesting that the size premium is not a substantial driver of the HML LTG portfolio returns. All estimates of SMB betas are statistically significant at a 95% confidence level or better. Conversely, the HML LTG portfolio returns do not exhibit statistically significant betas, at a 90% confidence level, for the HML (high minus low) or MOM (momentum) factors in any period. Beta estimates for both of these risk premia are close to zero in all post-formation periods.

The low or statistically insignificant estimated beta coefficients in Panel B, combined with a low R-squares for each model (maximum observed R-squared of 16.1%, see Table 11), suggest that the post-formation returns of the HML LTG portfolio are not substantially attributable to established risk premia. Given that the HML LTG portfolio produces consistently negative excess returns across post-formation periods and is largely uncorrelated with established risk premia, we assert that the portfolio performance is a product of market mispricing. In particular, our findings from Table 2 suggest that the significant negative alphas of the HML LTG portfolio are driven by market mispricing caused by analyst over-extrapolation of past growth rates.

Fundamental indices and LTG forecasts

We have identified the HML LTG portfolio as a proxy for market mispricing as induced by analyst forecast errors. We examine whether this is a major source of the excess returns of fundamental indices relative to market-cap indices. We do so by analysing LTG forecast characteristics of a variety of fundamental indices.

To construct fundamental indices, we merge Australian accounting data sourced from AH with monthly return data from the SPPR.[7] For comparability with Arnott et al. (2005), we consider four measures of company size independently in the construction of FIs. These measures are: (1) book value, (2) trailing 5-year average cash flow, (3) trailing 5-year average revenue, and (4) trailing 5-year average gross dividends. Similar to Arnott et al. (2005), we also construct a composite fundamental index which uses all four measures of company size.

The FIs are formed at the end of December each year and rebalanced after a 12-month period. The Australian financial year ends in 30 June. Therefore, we consider December to be a suitable month for rebalancing due to the availability of relevant accounting data.

To form portfolios, we rank each measure from highest to lowest value, selecting the largest 200 equity securities in the Australian market based on the aforementioned fundamental index measures. Portfolio weightings in constituent equities are in accordance with the magnitude of the respective measure. For the instance of the composite index, the rank is the average rank of the constituent measures. Where a firm does not form a part of one of the indices, a zero weight is assumed for that particular index. Table 5 presents the decomposition of the median and mean LTG EPS forecasts of constituent equities for the market-cap index and five fundamental indices.

On average 90.3% of the constituent equities for each strategy have accessible LTG EPS analyst forecast data. We note that constituents of the market-cap index exhibit median and mean LTG EPS forecasts of 10.30% and 10.52%, respectively. All FIs exhibit lower LTG EPS forecasts ranging from 9.39 to 10.21%. All FIs, except for the one based on book value, exhibit both median and mean LTG EPS forecasts of below 10%. The fundamental index based on revenue has the largest differential from the market index, with median and mean forecasts of 9.39% and 9.56%, respectively. The fundamental index based on book value exhibits statistically significantly lower median and mean LTG EPS forecasts of constituents than the market index at a 90% confidence level. All other FIs exhibit statistically significantly lower median and mean forecasts at a 99% confidence level.

The analysis of Table 5 reveals that the fundamental indices (Composite, Revenue, Dividend, Cash Flow, and Book Value) are systematically comprised of stocks with statistically significant lower median and mean LTG EPS forecasts when compared with the market portfolio. This suggests that fundamental indexation, through lower exposure to overvalued equities, likely outperforms the market capitalisation index.

Alpha of fundamental indices is statistically insignificant after controlling for analyst forecast errors

We have identified that analyst forecast errors are a significant source of market mispricing. and that fundamental indices have lower exposure to analyst forecast errors. Next, we assess whether a reduced exposure to AFE is the source of alpha for fundamental indexation. To investigate the source of the excess returns, we employ the following regression model as an extension to the Carhart model:

$$\begin{aligned}\mathrm{ExRet}_{it} = \alpha_{it} + \beta_{\mathrm{MKT}}\mathrm{MKT}_{\mathrm{t}} + \beta_{\mathrm{HML}}\mathrm{HML}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t \\ + \beta_{\mathrm{MOM}}\mathrm{MOM}_t + \beta_{\mathrm{LTG}}\mathrm{AFE}_t + \varepsilon_{it}\end{aligned} \tag{3}$$

Equation (3) extends the Carhart model through use of the additional factor AFE_t which identifies the excess return attributable to analyst forecast errors. The factor AFE_t represents the return of the hedging portfolio.

A positive and statistically significant alpha for FIs in Regression (2), contrasted with an insignificant alpha in Regression (3), would suggest that the excess return of FIs is attributable to a lower exposure to market mispricing than market-cap indexation.

Column (i) of Table 6 presents the alpha of our fundamental indexation strategies after application of the Carhart model (Eq. 2). Column (ii) and Column (iii) show results of an extended Carhart model that includes the monthly returns of a HML LTG portfolio as proxy for analyst forecast errors (Eq. 3).

For all fundamental indexation strategies (except of book value) we observe positive alphas, each statistically significant at the 99% confidence level. We note that FIs based on book value tend to perform poorly in the Australian stock market in our sample period. This result is in line with Mar et al. (2009) who similarly observe that their fundamental index based on book value is the only fundamental index

[7] We apply a 99% Winsorisation to the data post merge to reduce the effect of possibly spurious outliers.

Table 5 LTG forecast characteristics of constituent stocks for market indices and fundamental indices

Fundamental index type	Median estimate (%)	Mean estimate (%)	Lowest estimate (%)	Highest estimate (%)	Percentiles of LTG estimates				Std. Dev. estimate	Analyst coverage[a]
					5%	25%	75%	95%		
[1] Market (Cap-weighted) Index	10.31	10.52	5.44	16.17	−6.70	5.00	13.75	28.50	7.38	90.50%
[2] Fundamental index (Composite) *Difference [2]–[1]*	9.73–0.58***	9.94–0.59***	4.85–0.59***	15.57–0.59**	−7.70	4.90	13.00	27.26	7.34	91.95%
[3] Fundamental index (Revenue) *Difference [3]–[1]*	9.39–0.91***	9.56–0.96***	4.90–0.54***	14.74–1.43***	−7.20	5.00	12.70	26.00	6.77	90.17%
[4] Fundamental index (Dividend) *Difference [4]–[1]*	9.74–0.57***	9.98–0.54***	4.61–0.83***	14.96–1.21***	−4.90	5.00	13.10	26.10	6.50	89.20%
[5] Fundamental index (Cash Flow) *Difference [5]–[1]*	9.55–0.76***	9.74–0.78***	4.72–0.73***	15.29–0.87***	−7.72	4.90	12.90	27.26	7.22	89.66%
[6] Fundamental index (Book Value) *Difference [6]–[1]*	9.99–0.32**	10.21–0.31*	5.07–0.37**	15.92–0.25	−7.61	4.90	13.12	28.51	7.49	90.75%

The fundamental indices are comprised of stocks with statistically significant lower median and mean LTG EPS forecasts when compared to the market-cap weighted index. Since HML LTG portfolios generate significant negative alphas, the lower LTG EPS estimates of fundamental indices suggest that fundamental indices likely outperform the market-cap index. Statistical significance at the 1% level, 5% level, and the 10% level is denoted by ***, **, and *, respectively

[a]Analyst coverage represents the percentage of stocks with available IBES data for forecasted LTG in EPS at any point during the sample period. We note that this measure does not reflect the frequency of analyst coverage

Table 6 Excess return of fundamental indices with and without controlling for analyst forecast errors

Fundamental index type	Out-performance w/o controlling for analyst forecast errors	Out-performance controlling for $(\text{HML LTG})_{\text{Median}}$	Out-performance controlling for $(\text{HML LTG})_{\text{Mean}}$
	(i)	(ii)	(iii)
Fundamental index (Composite)	1.92%***	0.84%	0.60%
	(2.67)	(1.17)	(0.83)
Fundamental index Avg (ex-Composite)	2.04%***	0.72%	0.36%
	(2.83)	(1.00)	(0.50)
Fundamental index (Revenue)	2.52%***	1.56%	1.68%
	(2.63)	(1.18)	(1.75)
Fundamental index (Dividend)	2.04%***	0.84%	0.96%
	(3.40)	(0.78)	(0.89)
Fundamental index (Cash Flow)	3.36%***	0.48%	0.48%
	(3.50)	(0.44)	(0.44)
Fundamental index (Book Value)	0.36%	0.60%	0.72%
	(0.30)	(0.50)	(0.60)

Column (i) presents the annual alpha of each fundamental index when employing the standard Carhart model (Eq. 2). Column (ii) and Column (iii) present the alpha of each fundamental index when employing a Carhart model extended to control for median (Column (ii)) and mean (Column (iii)) analyst forecast errors (Eq. 3). Standard errors are clustered by month. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated *t*-statistics in parentheses

not to generate a significant positive alpha in a Carhart regression.

The extension of the Carhart model to include one additional factor to proxy for analyst forecast errors results in all previously positive and statistically significant alphas to become uniformly statistically insignificant for all fundamental indexation strategies examined. Our findings suggest that a large proportion of the alpha from FIs are attributable to analyst forecast errors, specifically the overextrapolation of past growth rates. Intuitively, since the HML LTG portfolio generates negative alphas when analysed using a Carhart model, we expect fundamental indices to exhibit negative factor loadings for the proxy of analyst forecast errors in Eq. 3. Consistent with these expectations, Table 7 presents related results.

Table 7 shows the factor loadings for three extensions of the Carhart model in Eq. 2, where each extension represents the addition of one of the following factors: a HML LTG portfolio constructed on median LTG EPS estimate (Column (i)), a HML LTG portfolio constructed on mean LTG EPS estimate (Column (ii)), and the average LTG EPS forecast across all equities in the examined fundamental index (Column (iii)).

Consistent with our expectations we observe negative and statistically significant factor loadings on the additional regressor for all fundamental indices, except for book value. As discussed for Table 5, constituents of the fundamental index based on book value exhibit the smallest differences in LTG EPS forecasts when compared to the market-cap index out of all examined fundamental indices.

The negative factor loadings of the proxy for analyst forecast errors as shown in Table 7, combined with the disappearance of statistically significant alphas shown in Table 6, provide strong support that FIs outperform market-cap indices through lower exposure to adverse market mispricing.[8]

Exposures of fundamental indices and the market index to analyst forecast errors

We have observed that the alpha of fundamental indexation becomes statistically insignificant after controlling for market mispricing induce by AFE. However, it is important to examine whether analyst overextrapolation of strong past performance or weak past performance is a stronger source of market mispricing. Table 8 contrasts the relative exposures of the FIs versus the market index to above and below median LTG equities. We define *negative market extrapolation* to be the proportion of stocks in an index that exhibit below median LTG EPS forecasts. These stocks are expected to be *ex ante* undervalued. We define *positive market extrapolation* as the proportion of stocks in an index that exhibit

[8] We note that book value is the only FI that exhibits a statistically significant negative relation with GR5YR(EPS). We suspect there is a size effect influencing this result. The largest companies in the Australian market are long-established banking and mining companies. These larger, more mature companies are likely to have higher book values and lower future growth rates due to their position in their business life cycles. Hence, we do expect a statistically significant negative relation between book value and GR5YR(EPS)

Table 7 Fundamental indices and analyst forecast errors

Fundamental index type	HML *Median* LTG (i)	HML *Mean* LTG (ii)	GR5YR(EPS) (iii)
Fundamental index (Composite)	− 0.1155***	− 0.1045***	− 0.0870
	(− 4.2865)	(− 3.9657)	(− 1.4790)
Fundamental index Avg (ex-Composite)	− 0.1145***	− 0.1034***	− 0.0842
	(− 4.1025)	(− 3.8076)	(− 1.4106)
Fundamental index (Revenue)	− 0.1923***	− 0.1945***	− 0.1038
	(− 4.9326)	(− 5.0722)	(− 1.3493)
Fundamental index (Dividend)	− 0.1948***	− 0.1781***	0.0228
	(− 3.7867)	(− 3.6584)	(0.2263)
Fundamental index (Cash Flow)	− 0.1288***	− 0.1104**	− 0.0669
	(− 2.6549)	(− 2.3629)	(− 0.7637)
Fundamental index (Book Value)	0.0581	0.0696	− 0.1891**
	(1.1304)	(1.3289)	(− 2.3996)
Std. errors (clustered)	Yes	Yes	Yes
Controls: MKT-Rf, SMB, HML, MOM	Yes	Yes	Yes

The factor loadings are estimated using three separate regressions as extensions to the Carhart model where one additional factor is added in each case. By estimating factor loadings while controlling for systematic risk, SMB, HML, and MOM factors, the potential for omitted variables to bias estimated factor loadings is mitigated. HML *Median* LTG (Column (i)) and HML *Mean* LTG (Column (ii)) portfolios each consist of a long position in equities with above median LTG in EPS forecasts and a short position in equities with below median LTG in EPS forecasts, using median and mean analyst forecasts, respectively. GR5YR (EPS) is the analyst forecasted 5-year growth rate in EPS (Column (iii)). All of the fundamental indices examined, except for book value, exhibit statistically significant negative factor loadings for the HML LTG factors at the 99% confidence level. Only the fundamental index based on book value is found to have a statistically significant loading on the GR5YR(EPS) factor. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively. Standard errors are clustered by month

Table 8 Exposures of fundamental indices and market-cap index to positive and negative market extrapolation

Fundamental index type	Negative market extrapolation [$E(g)$ < Median($E(g)$)]			Positive market extrapolation [$E(g)$ > Median($E(g)$)]			Exposure to above median LTG EPS forecast stocks compared to market-cap index
	Weights$_{FI}$ (i)	Weights$_{MKT}$ (ii)	Difference (Weights) (iii)	Weights$_{FI}$ (iv)	Weights$_{MKT}$ (v)	Difference (Weights) (vi)	(vii)
Fundamental index (Composite)	34.87%	29.55%	5.32%***	35.83%	44.67%	− 8.83%***	− 14.16%***
	(0.000)	(0.000)		(0.000)	(0.000)		
Fundamental index (Revenue)	34.07%	29.01%	5.06%***	37.25%	44.32%	− 7.07%***	− 12.14%***
	(0.000)	(0.000)		(0.000)	(0.000)		
Fundamental index (Dividend)	41.90%	31.15%	10.74%***	31.97%	41.87%	− 9.90%***	− 20.65%***
	(0.000)	(0.000)		(0.000)	(0.000)		
Fundamental index (Cash Flow)	35.44%	29.81%	5.63%***	35.72%	44.21%	− 8.48%***	− 14.12%***
	(0.000)	(0.000)		(0.000)	(0.000)		
Fundamental index (Book Value)	30.49%	30.01%	0.48%	37.56%	44.06%	− 6.49%**	− 6.97%**
	(0.000)	(0.000)		(0.000)	(0.000)		

Negative (positive) market extrapolation refers to stocks with below (above) median LTG EPS forecasts. Column (iii) shows the increased exposure of fundamental indices, relative to the market-cap index, to below median LTG EPS forecast stocks that are expected to outperform in future periods. Column (vi) shows the reduced exposure of fundamental indices, relative to the market-cap index, to above median LTG EPS forecast stocks that are expected to underperform in future periods. The net reduction in exposure of fundamental indices to unfavourable market mispricing is shown in column (vii). The sum of portfolio weights for positive and negative market extrapolation is less than one due to some index constituents lacking analyst LTG EPS forecast data in various periods. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated p-values in parentheses

Table 9 Decomposition of source of fundamental indexation alpha

Fundamental index type	Drivers of the difference in annual returns between fundamental indices and the market index		
	Jensen's alpha	Δ(Returns) induced by negative-Extrapolation [$E(g)$ < Median($E(g)$)]	Δ(Returns) induced by positive-Extrapolation [$E(g)$ > Median($E(g)$)]
	(i)	(ii)	(iii)
Fundamental index (Composite)	2.02%***	1.03%***	−0.02%
	(0.002)	(0.004)	(0.511)
Fundamental index (Revenue)	3.04%***	1.41%***	0.50%
	(0.001)	(0.003)	(0.215)
Fundamental index (Dividend)	1.88%**	1.17%**	−0.83%
	(0.042)	(0.036)	(0.864)
Fundamental index (Cash Flows)	2.57%***	1.07%**	0.51%
	(0.002)	(0.015)	(0.235)
Fundamental index (Book Value)	0.97%	0.59%*	−0.06%
	(0.323)	(0.086)	(0.529)

Negative (positive) market extrapolation refers to stocks with below (above) median LTG EPS forecasts. The table shows that the proportion of the outperformance of fundamental indices, relative to market-cap indexation, that is attributable to reduced exposure to analyst forecast errors is entirely driven by the increased weighting of fundamental indices to undervalued firms. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated *p*-values in parentheses

above median LTG EPS forecasts. These stocks are expected to be *ex ante* overvalued.

All fundamental indices, except book value, exhibit significantly higher exposure than the market index to below median LTG EPS firms (undervalued stocks).[9] These significant differences range from 5.06 to 10.74%. In addition, each fundamental index is comprised of statistically significantly lower exposures to above median LTG EPS forecast equities (overvalued stocks), at a 95% or greater confidence level.

Fundamental indexation and exposure to undervalued securities

With FIs having substantial compositional differences from the market-cap index with respect to both above and below median LTG EPS forecast stocks, one open question is whether the outperformance of fundamental indices is predominately driven by higher exposure to undervalued stocks, lower exposure to overvalued stocks or a combination of both.

Table 9 decomposes the alpha of examined fundamental indexation strategies into the proportions attributable to positive and negative extrapolation. The table indicates that 50–60% of the abnormal return (Column (i)) of the fundamental indices is explained by the over-weighting (relative to the market-cap index) of stocks previously exposed to over-extrapolation of poor EPS growth rates (Column (ii)). By contrast, the under-weighting of stocks exposed to over-extrapolation of strong EPS growth rates does not drive the outperformance of fundamental indexation (Column (iii)), with a statistically insignificant impact observable across all fundamental indices. This is consistent with FIs in Australia having a small-value tilt (see Mar et al. 2009), with HML betas ranging from 0.03 for dividend-based fundamental indices to 0.16 for book value-based fundamental indices (see Appendix, Table 12). It is also possible that the overweighting of "out-of-favour" securities in fundamental indices might cause these indices to drift toward securities that are more likely to be exposed to bankruptcy risk during periods of market dislocation. In this case, the outperformance of fundamental indices could represent a rational compensation for taking on greater drawdown risk (see e.g. Kantos and DiBartolomeo 2020). To the extent that such bankruptcy risk is priced by the premium on the HML factor, we do not expect this explanation to drive our results on the risk-adjusted outperformance of the fundamental indices considered in our study.

[9] We believe the asymmetric weight distribution may be the result of large-cap companies (such as banks, utilities, and other listed infrastructure) in the Australian market with a high book value and steady predictable earnings. Such companies would be weighted in a book-based FI at a similar rate to a cap-weighted index. Conversely, any "growth stocks" are likely to be underrepresented as this is where a large gap between book value and market capitalisation will emerge

Table 10 Enhancement of fundamental index returns through reduction of exposure to analyst forecast errors

Fundamental index type	Out-performance *without* AFE enhancement	Out-performance of *with* AFE enhancement	Fundamental index enhancement (yearly difference)
Fundamental index (Composite)	1.81%***	2.88%***	1.07%***
	(3.00)	(3.21)	
Fundamental index (Revenue)	3.12%***	3.72%***	0.61%***
	(3.25)	(3.21)	
Fundamental index (Dividend)	2.76%**	4.08%***	1.32%***
	(2.09)	(3.05)	
Fundamental index (Cash Flow)	2.76%**	3.24%***	0.48%***
	(2.56)	(3.04)	
Fundamental index (Book Value)	0.72%	1.08%	0.36%
	(0.60)	(1.20)	

This table shows increased alphas of fundamental indexation strategies when investment weights are rescaled to reduce index exposure to analyst forecast errors (AFE). In each case alpha is estimated based on the Carhart model. As shown, the performance of all of the fundamental indices, except for book value, can be significantly enhanced through the reduction of exposure to AFE. Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated *t*-statistics in parentheses

Fundamental indices can be reweighted based on AFE to enhance performance

We have shown that the risk-adjusted outperformance of fundamental indexation relative to market-cap indexation is largely attributable to reduced exposure to analyst forecast errors. A natural extension to this important finding is to examine whether or not the performance of fundamental indexation can be enhanced through reduction of exposure to analyst forecast errors by deliberately reweighting the index.[10]

For each variant of fundamental indexation we select the top 200 ranked firms in the same manner as previously described. Instead of weighting the portfolio in accordance with magnitude of the fundamental measure of each firm, we weight the fundamental indexation portfolio in proportion to the inverse of each stock's forecasted LTG rate.[11] The inverse of a stock's forecasted LTG rate is calculated as:

$$\mathrm{InvLTG}_i = \frac{1}{\left(1 + \mathrm{LTG}_i\right)} \tag{4}$$

where InvLTG_i is the inverse of the analyst LTG rate of stock *i* (denoted LTG_i). The stock's new weight in the enhanced fundamental index is therefore calculated as:

$$\mathrm{Wgt}_i = \frac{\mathrm{InvLTG}_i}{\sum_1^{200} \mathrm{InvLTG}_i} \quad \text{subject to} \sum_1^{200} \mathrm{Wgt}_i = 1 \tag{5}$$

where Wgt_i is the portfolio investment weighting in stock *i*. In the instance where a stock lacks available analyst LTG forecast data InvLTG_i takes on a value of zero. Similar to the construction of the standard fundamental indices discussed previously, annual rebalancing occurs in December of each year. Table 10 shows the alphas of various fundamental indices derived from the Carhart model with and without "AFE enhancement", i.e. reduced exposure to analyst forecast errors.

For all of the FIs (except book value), our AFE rescaling reduces exposure to analyst forecast errors and results in a statistically and economically significant increase of alpha. The alpha enhancement is statistically significant at a 99% confidence level for each of the fundamental indices except book value. Given that portfolios formed on median analyst LTG forecasts are market-valuation-indifferent, this critical finding could be considered an alternate form of fundamental indexation not yet explored in the literature.

[10] In Tables 13, 14, 15 we report a detail analysis of the economic and statistica significance of analysts' forecast errors over different time horizons (short term forecasts and lont term forecasts). Table 13 shows the extent of analysts' forecast errors in estimating firm's long-term growth rates (LTG). Table 14 reports the extent of analysts' forecast errors in estimating 1-year-ahead (FY1) earnings per share (FE), while Table 15 shows the extent of analysts' forecast revisions of previous 1-year-ahead (FY1) estimated of earnings per share (FR). The evidence in these tables confirms the existence of large and significant errors in analysts' forecasts, and highlights the importance of constructing indices that are less exposed to market errors in expectations and any subsequent revision in such expectations.

[11] We opted for this simplistic weighting scheme to be conservative and prevent portfolio concentration. To provide some intuition, if two stocks had LTG rates of 3% and 30%, respectively, whilst the remaining 198 stocks had LTG rates of 10%, then the lowest LTG stock would have a weighting of only 1.26x that of the highest LTG stock.

Conclusion

Motivated by the increasing demand for passive investment strategies in ever growing global capital markets and the documented outperformance of fundamental indexation when compared to traditional market cap-weighted indexation in many capital markets including Australia (Mar et al. 2009), this paper investigates the drivers of the outperformance of fundamental indexation.

Our analysis, with a focus on the Australian context, extends the seminal work of Arnott et al. (2005) who asserts that market mispricing may be a source of the observed outperformance of fundamental indexation. This study's main contribution is to identify a specific form of market mispricing and show how a reduced exposure of fundamental indexation to analyst forecast errors drives the strategy's relative outperformance versus market-cap indexation. To our knowledge, our study is the first to investigate AFE-induced market mispricing as the source of the *ex post* outperformance of fundamental indexation.

Our analysis provides several novel results. We find that fundamental indexation results in the construction of portfolios for which constituent stocks, on average, exhibit lower median analyst LTG forecasts than the constituents of market-cap weighted indices. We also find that a high-minus-low (HML) portfolio of analyst LTG forecasts generates significant negative alphas in each of five post-formation years examined in our analysis. This is consistent with our findings of mean reversion in LTG forecasts, which suggests that analysts over-extrapolate past returns when projecting stocks' future growth rates. These results provide support to our hypothesis that fundamental indices exhibit systematically lower expectation errors than the cap-weighted index.

We also find that excess returns of fundamental indexation can be accounted for through adjustments for analyst errors in expectations. Our analysis shows that using the Carhart model, four of the five examined fundamental indices generate significant alphas across our sample period. However, once the exposure of fundamental indices to analyst forecast errors is accounted for, alphas across all fundamental indices become statistically insignificant. Interestingly, while the fundamental indices relative to the market-cap index have both lower exposure to overvalued stocks and higher exposure to undervalued stocks, it is the increased exposure to undervalued stocks that drives almost entirely the outperformance of fundamental indexation. As an important result for investors we show that the performance of fundamental indices can be enhanced through recalibrating portfolio weights to reduce exposure to analyst forecast errors.

It is conceivable that there remain independently insignificant factors contributing to the outperformance of fundamental indexation. To explain why fundamental indexation generates lower returns than market-cap indexation in some periods despite on average generating significant positive alphas, future research could complement our analysis by exploring funding illiquidity and beta compression as examined by Frazzini and Pedersen (2014).

Appendix

See Tables 11, 12, 13, 14, 15.

Table 11 Excess returns and factor loadings for high minus low (HML) hedging portfolios

	1 year ahead			3 year ahead			5 year ahead		
	CAPM	3 Factor	4 Factor	CAPM	3 Factor	4 Factor	CAPM	3 Factor	4 Factor
Alpha (p.a.)	−0.0780***	−0.0828***	−0.0876***	−0.0516***	−0.0588***	−0.0576***	−0.0468***	−0.0552***	−0.0564***
	(0.0204)	(0.0216)	(0.0216)	(0.0132)	(0.0144)	(0.0144)	(0.0120)	(0.0132)	(0.0132)
Beta	0.2265***	0.2095***	0.2184***	0.2497***	0.2422***	0.2415***	0.2684***	0.2548***	0.2563***
	(0.0492)	(0.0489)	(0.0496)	(0.0309)	(0.0315)	(0.0319)	(0.0298)	(0.0301)	(0.0305)
SMB		0.0944***	0.1053***		0.0508**	0.0500**		0.0712***	0.0731***
		(0.0362)	(0.0376)		(0.0223)	(0.0232)		(0.0200)	(0.0207)
HML		0.0156	0.0283		0.0551	0.0543		0.0620	0.0636
		(0.0757)	(0.0766)		(0.0486)	(0.0490)		(0.0449)	(0.0451)
MOM			0.0403			−0.0031			0.0076
			(0.0381)			(0.0239)			(0.0213)
R-squared	11.4%	15.6%	16.1%	12.6%	13.5%	13.6%	11.1%	12.8%	12.8%

This appendix presents additional details related to Table 4 by comparing the results of CAPM, Fama-French, and Carhart regressions on the post-formation returns of high minus low (HML) portfolios formed on median analyst forecasts of long-term growth (LTG) in earnings per share (EPS). Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated standard errors in parentheses

Table 12 Excess performance of various fundamental indices with and without controlling for analyst forecast errors

	Composite		Revenue		Dividend		Cash Flow		Book Value	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Alpha (p.a.)	0.0192***	0.0084	0.0021***	0.0013	0.0017***	0.0007	0.0028***	0.0004	0.0003	0.0005
	(0.0006)	(0.0006)	(0.0008)	(0.0011)	(0.0005)	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0010)
Beta	0.9696***	0.9899***	0.9263***	0.9585***	0.9330***	0.9732***	0.9876***	1.0076***	1.0366***	1.0241***
	(0.0174)	(0.0215)	(0.0218)	(0.0263)	(0.0244)	(0.0262)	(0.0258)	(0.0299)	(0.0292)	(0.0298)
SMB	−0.0111	−0.0039	−0.0137	−0.0023	−0.0123	0.0020	−0.0244	−0.0173	0.0044	−0.0000
	(0.0115)	(0.0126)	(0.0135)	(0.0146)	(0.0225)	(0.0243)	(0.0194)	(0.0208)	(0.0212)	(0.0218)
HML	0.0812***	0.0821***	0.1152***	0.1167***	0.0320	0.0339	0.0036	0.0045	0.1578***	0.1572***
	(0.0213)	(0.0217)	(0.0308)	(0.0311)	(0.0310)	(0.0288)	(0.0314)	(0.0322)	(0.0410)	(0.0403)
PR1YR	−0.0547***	−0.0520***	−0.0749***	−0.0707***	−0.0504**	−0.0451**	−0.0449***	−0.0423***	−0.0544***	−0.0560***
	(0.0121)	(0.0113)	(0.0156)	(0.0143)	(0.0195)	(0.0182)	(0.0154)	(0.0150)	(0.0189)	(0.0194)
$F(HML\ LTG)_{Median}$		−0.1015***		−0.1605***		−0.2005***		−0.1001**		−0.0620
		(0.0289)		(0.0385)		(0.0417)		(0.0451)		(0.0464)
Std. Errors (clustered)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	96.9%	97.1%	93.9%	94.6%	90.7%	91.8%	93.6%	93.8%	93.2%	93.2%

This appendix presents additional details related to Table 6. For each fundamental index (Composite, Revenue, Dividend, Cash Flow, Book Value) two columns are presented. The first column shows the alpha and factor loadings when employing the standard Carhart model (Eq. 2). The second column shows the alpha and factor loadings when employing the extended Carhart model controlling for analyst forecast errors (Eq. 3). Statistical significance at the 1% level and the 5% level is denoted by *** and **, respectively, with associated *t*-statistics in parentheses. Standard errors are clustered by month

Table 13 Growth characteristics of portfolios formed on the basis of the fundamental variables

	Lowest									Highest
	1	2	3	4	5	6	7	8	9	10
A. Ranking on Book-to-Market										
Past EPS growth	22.89	19.54	17.27	14.65	12.95	10.64	10.44	8.34	5.37	− 0.69
Forecast EPS growth	24.64	20.52	18.28	16.55	15.89	14.06	12.04	11.73	12.05	11.51
Estimated future EPS growth	9.72	8.21	8.18	6.42	5.47	6.14	5.42	4.42	3.34	6.35
Forecast Errors (LTG)	14.92	12.32	10.10	10.13	10.42	7.92	6.62	7.31	8.71	5.17
B. Ranking on Sales-to-Price										
Past EPS growth	− 4.30	11.24	13.69	12.79	12.90	12.50	12.66	13.88	14.85	19.45
Forecast EPS growth	22.28	21.46	18.43	17.10	15.09	14.96	13.82	12.22	12.01	11.94
Estimated future EPS growth	33.58	12.49	8.28	5.60	5.68	4.80	4.48	2.86	0.44	− 2.33
Forecast Errors (LTG)	− 11.30	8.96	10.15	11.50	9.41	10.16	9.35	9.36	11.57	14.27
C. Ranking on Cash Flow-to-Price										
Past EPS growth	9.60	12.67	12.04	11.38	10.39	9.65	9.86	9.85	10.76	11.15
Forecast EPS growth	26.23	20.28	17.73	16.78	15.59	14.82	13.64	12.12	11.99	12.44
Estimated future EPS growth	19.62	10.87	6.86	9.56	5.46	8.23	4.36	2.02	1.66	0.54
Forecast Errors (LTG)	6.60	9.41	10.87	7.21	10.13	6.59	9.28	10.10	10.33	11.90
D. Ranking on Dividend-to-Price										
Past EPS growth	10.39	15.01	12.35	11.65	10.66	11.62	11.14	11.71	12.02	10.50
Forecast EPS growth	25.50	22.69	19.64	17.48	17.46	15.64	15.67	12.86	12.29	12.95
Estimated future EPS growth	20.40	11.54	7.20	10.44	6.97	8.64	6.20	2.29	0.95	0.75
Forecast Errors (LTG)	5.10	11.15	12.43	7.04	10.49	7.00	9.47	10.57	11.34	12.20

The sample covers the period between 1993 and 2013 and consists of firms that have analysts' forecasts of EPS growth available on I/B/E/S. Portfolios are formed annually in ascending order on the basis of the fundamental variables in the month following the announcement of annual earnings. The fundamental variables are book-to-market, sales-to-price, dividend-to-price, and cash-to-price. Future EPS growth is obtained by fitting an ordinary least squares regression through the logarithm of the most recently reported earnings-per-share and the five future years of annual earnings-per-share. Past EPS growth is obtained by fitting an ordinary least squares regression through the logarithm of the six most recently reported earnings-per-share. Forecast EPS growth is the median analysts' estimate of earnings-per-share growth over the next five years (LTG) as measured in the I/B/E/S statistical month spanning the announcement of annual earnings

Table 14 Magnitude of analyst forecast errors (FY1)—full sample

Months to EPS Announcement	Number obs.	Median FE_A (1y ahead)	Mean FE_A (1y ahead)	Median FE_B (1y ahead)	Mean FE_B (1y ahead)	Number Estimates	Number Upward Estimates	Number Downward Estimates	Percentage of Analysts' Disagreement
Announcement - 8 months	7940	0.4653	0.4677	0.018	0.0178	5.9	2	2.3	29.30%
Announcement - 7 months	7940	0.4043	0.4155	0.0158	0.0154	5.9	2.2	2.6	25.90%
Announcement - 6 months	7940	0.325	0.3327	0.0129	0.0126	5.8	2.6	2.7	24.70%
Announcement - 5 months	7940	0.2824	0.2889	0.0113	0.0111	5.8	2.1	2.3	33.30%
Announcement - 4 months	7940	0.2268	0.2394	0.0089	0.0087	5.7	1.9	2.3	32.90%
Announcement - 3 months	7940	0.1858	0.1928	0.0079	0.0077	5.6	1.9	2.3	41.20%
Announcement - 2 months	7940	0.1971	0.205	0.007	0.0067	5.5	1.9	2.2	22.40%
Announcement - 1 month	7940	0.1439	0.1527	0.0061	0.006	5.4	2.2	2.2	22.70%
Diff(1m–8m)		−0.3213***	−0.3150***	−0.0119***	−0.0117***				

This table reports differences in medians (means) and the corresponding median (mean) difference tests for analysts' forecast errors (FE) over the entire sample ranging from 1993 to 2013. The forecast error FE_A is defined as the difference between the median forecast of fiscal year *N* earnings per share made eight months before the FYE month *t* ($F_{t\text{-}8}$(AN)) and the actual earnings (AN) deflated by the actual *earnings (*AN), i.e. $FE_B = [F_{t\text{-}8}(\text{AN}) - \text{AN}t_1]/\text{AN}_t$. The forecast error FE_B is defined as the difference between the median forecast of fiscal year *N* earnings per share made eight months before the FYE month *t* (F_{t-8}(AN)) and the actual earnings (AN) deflated by the stock price at the beginning of the fiscal year retrieved from the I/B/E/S database, i.e. $FE_B = [F_{t-8}(\text{AN}) - \text{AN}]/P_{t-11}$. All other forecast errors reported in the table are computed similarly in other months preceding the earnings announcement (*Announcement*). The sorting procedure was conducted annually at the end of the fiscal year preceding the analysts' forecasts

Table 15 Magnitude of analyst forecast revisions (FY1)—full sample

Months to EPS Announcement	Number obs.	Median FR (1yr ahead)	Mean FR (1yr ahead)	Number of estimates	Number upward estimates	Number downward estimates	Percentage of analysts' disagreement
Announcement - 8 months	7940	–	–	5.9	2	2.3	29.30%
Announcement - 7 months	7940	−0.0317	−0.0292	5.9	2.2	2.6	25.90%
Announcement - 6 months	7940	−0.0813	−0.0777	5.8	2.6	2.7	24.70%
Announcement - 5 months	7940	−0.1527	−0.1452	5.8	2.1	2.3	33.30%
Announcement - 4 months	7940	−0.1727	−0.1677	5.7	1.9	2.3	32.90%
Announcement - 3 months	7940	−0.2643	−0.2552	5.6	1.9	2.3	41.20%
Announcement - 2 months	7940	−0.2849	−0.2759	5.5	1.9	2.2	22.40%
Announcement - 1 month	7940	−0.2866	−0.2878	5.4	2.2	2.2	22.70%
Diff(Announcement - 7m)		0.0316***	0.0292***				

This table reports differences in medians (means) and the corresponding median (mean) difference tests for analysts' forecast revisions (FR) over the entire sample ranging from 1993 to 2013. The forecast revision FR_k is defined as the difference between the median forecast (F) of fiscal year N actual earnings per share (AN) made k (with $1 \le k \le 7$) months before the FYE month t (F_{t-k}(AN)) and median (F) of fiscal year N actual earnings per share (AN) made eight months before the FYE month t (F_{t-8}(AN)) deflated by the stock price at the beginning of the fiscal year retrieved from the I/B/E/S database, i.e. $FR_k = [F_{t-k}(AN) - F_{t-8}(AN)]/P_{t-11}$. The sorting procedure was conducted annually at the end of the fiscal year preceding the analysts' forecasts

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