1. Harnessing Investor Sentiment Using Big Data Analytics
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1. Harnessing Investor Sentiment Using Big Data Analytics
This study examines the statistical and economic significance of investor sentiment, based on general business news, on stock market returns and volatility. Using big data analytics, our findings reveal that sentiment does not affect market returns. However, sentiment does influence volatility, with negative (positive) sentiment increasing (decreasing) volatility. Investor sentiment is also economically significant; we demonstrate that an ETF-based trading strategy can be used to capitalize on the predictive capability of investor sentiment. This paper summarizes the research findings made by Johnman, Vanstone and Gepp (2018) from a more practical perspective.

In today’s highly connected world, investors have access to daily financial and general business news updates, which collectively have the power to shape financial markets. This information is best described as ‘investor sentiment’, namely, the attitude(s) investors have towards financial assets, such as stocks or commodities. Until recently, investor sentiment was largely viewed as a wild beast, moving unpredictably despite experts’ attempts to forecast the direction and magnitude of its effects. Today, thanks to big data analytics, we are entering a new era in which it may be possible to do the unthinkable: harness the beast.

Academic research broadly classifies investors as either ‘noise traders’ (retail investors with random beliefs about future returns) or ‘rational arbitrageurs’ (sophisticated investors who hold more informed beliefs about future returns) (De Long et al., 1990). Investor sentiment research typically measures sentiment using textual data from financially focused news sources, such as The Wall Street Journal, which are more likely to be read by and influence sophisticated investors. The seminal papers of Tetlock (2007) and Tetlock, Saar-Tsenchansky and Macskassy (2008), further expanded by Ferguson et al. (2015), show that investor sentiment is capable of predicting asset prices, with positive (negative) sentiment predicting positive (negative) financial returns. Additionally, positive (negative) investor sentiment has been shown to decrease (increase) volatility in financial returns (Kumari and Mahakud, 2015). Negative sentiment’s effect on financial returns and volatility is usually found to be stronger than positive sentiment. Furthermore, news-based trading strategies can be developed to demonstrate the economic significance of the effects of investor sentiment on financial returns and volatility. This study extends prior work by examining the statistical and economic effect of sentiment, derived from business news published by the Guardian Media Group, on market returns and volatility. In contrast to previous literature, the data source used in this study is more likely to influence the investment choices of retail investors, who often do not have access to more financially focused news sources, such as Bloomberg. This allows us to gain insight into the effects of retail investor sentiment on market returns and volatility.
Use of Sentiment Analysis to Predict Financial Markets: An Overview

Using sentiment analysis in the context of a financial market usually comprises three key components: data sources, the sentiment analysis process, and a trading strategy. The sentiment analysis process involves extracting sentiment information from textual data and representing it in a numerical format, which we refer to as a sentiment analysis metric (SAM). Some of the literature stops at this point, merely examining the statistical significance of a SAM. However, this study also employs a trading strategy – rules to make trading decisions based on the SAM – to ascertain its economic significance.

Data Sources

The data sources comprise both the textual data for measurement of sentiment and the financial markets data for evaluation purposes. A range of textual data sources have been used, including news articles from prominent newspapers, message and discussion boards, Twitter, corporate announcements, macro-economic news announcements, and company annual reports. Financial markets data are typically stocks from major indexes (e.g. S&P 500), but have also included currency exchange rates and gold futures.

Sentiment Analysis Process

The sentiment analysis process involves three stages, namely feature extraction, feature representation and sentiment classification. In the feature extraction phase, features (variables) representative of investor sentiment are extracted from the text (typically as discrete words or phrases). These features are subsequently represented in a numerical format (e.g. the number of times a word appears). Finally, the sentiment classification phase involves processing the represented features to determine whether the text displays positive or negative sentiment. This processing often involves matching the features to a dictionary consisting of words that are pre-classified as being associated with positive or negative sentiment. Machine learning techniques, such as support vector machines or neural networks, are also often used during the sentiment classification phase.

Trading Strategy

The final component of the sentiment analysis process is the use of a trading strategy. A variety of trading strategies have been employed, including buying (or selling) an asset when a SAM is positive (or negative), or taking a long (or short) position in assets in the top (or bottom) section of investor sentiment rankings based on a SAM. The majority of trading strategies utilize short timeframes, typically daily or intraday (e.g. 20 minutes).

Utilizing Big Data Analytics to Conduct Sentiment Analysis

This study utilizes a dataset of 79,823 business news articles published by the Guardian Media Group between 02/01/2002 and 01/06/2016. The Guardian Media Group is a UK mass media group that publishes newspapers, including The Guardian, The Observer, and The Guardian Weekly. As the data source is a UK-based company with a large UK audience, the FTSE 100 is used as the source of financial markets data. Since the FTSE 100 cannot be directly traded, BlackRock’s iShares Core FTSE 100 UCITS ETF (ISF) is utilized for the trading strategy. The FTSE 100 and ETF data for the sample period are sourced from Bloomberg.

Statistical and Economic Significance of Sentiment on Stock Market Returns and Volatility

Linear regression models are employed to measure the statistical significance of positive and negative sentiment (i.e. the SAMs) on daily excess returns and volatility in the FTSE 100 (Table 1). While sentiment has no discernable effect on returns, it does have a statistically significant effect on volatility, with negative (positive) sentiment increasing (decreasing) volatility. This suggests that the...
behavior of retail investors based on sentiment does not influence market returns, but can add additional noise to the market, which increases volatility and may cause prices to temporarily deviate from their fundamental values. It also highlights that sentiment measurements created from data sources targeted towards different types of investors can have different effects on financial markets. For example, Ferguson et al. (2015) and Tetlock, Saar-Tenschansky and Macskassy (2008) find that sentiment metrics created from data sources more likely to be read by sophisticated investors (e.g. Financial Times) have a statistically significant effect on market returns.

### TABLE 1: EFFECTS OF POSITIVE AND NEGATIVE SENTIMENT ON DAILY EXCESS RETURNS (PANEL A) AND DAILY VOLATILITY (PANEL B) IN THE FTSE 100

#### Panel A: Daily Excess Returns

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>T-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.00008927</td>
<td>-0.437</td>
<td>0.662</td>
</tr>
<tr>
<td>Std_Positive</td>
<td>0.00006195</td>
<td>0.309</td>
<td>0.757</td>
</tr>
<tr>
<td>Std_Negative</td>
<td>0.00001652</td>
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<td>0.930</td>
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<tr>
<td>F-Statistic</td>
<td>0.048</td>
<td>0.953</td>
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</table>

#### Panel B: Volatility

<table>
<thead>
<tr>
<th>Volatility Proxy</th>
<th>(Ri)² Coefficient</th>
<th>T-Statistic</th>
<th>P-Value</th>
<th>Hi – Li Coefficient</th>
<th>T-Stat</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.0001467</td>
<td>20.144</td>
<td>0.000 **</td>
<td>76.6704</td>
<td>101.375</td>
<td>0.000 **</td>
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<tr>
<td>Std_Positive</td>
<td>-0.0000175</td>
<td>-2.442</td>
<td>0.015 *</td>
<td>-2.4163</td>
<td>-3.255</td>
<td>0.001 **</td>
</tr>
<tr>
<td>Std_Negative</td>
<td>0.0000548</td>
<td>8.206</td>
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<td>11.3370</td>
<td>16.338</td>
<td>0.000 **</td>
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<tr>
<td>F-Statistic</td>
<td>46.770</td>
<td>0.000 **</td>
<td></td>
<td>169.600</td>
<td>0.000 **</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Panel B presents the results of two volatility proxies used in prior research: squared returns (Ri)² and high-low range (Hi – Li). Statistical significance is denoted by * (5% level) and ** (1% level).
To determine the economic significance of these results, this study implements a short-term reversal trading strategy. The Active Strategy aims to exploit the additional volatility caused by retail investors by entering a trade when prices appear to have diverged from their fundamental values and exiting when they revert back. Specifically, the Active Strategy enters a trade at market close if the Std_Negative value for the day, calculated using news from the previous trading day’s close to today’s open, is greater than the 70th quantile of its values in the prior calendar year. The threshold ensures the strategy only takes positions when sentiment is substantially negative. Each trade uses all available equity and is exited at the market close of the day on which Std_Negative value falls below the 70% threshold.

As shown in Figure 1 and discussed in Johnman, Vanstone and Gepp (2018), the Active Strategy outperforms a simple Buy and Hold Strategy on both a risk-adjusted and absolute basis. The Active strategy has a larger Sharpe Ratio than the Buy and Hold Strategy, exhibiting higher returns and lower risk, as well as lower drawdown. Additionally, the Active Strategy’s average daily return for the days in which it is in the market is greater than that of the Buy and Hold Strategy. These results do not factor in practical market constraints such as transaction costs.
Conclusion

This study provides insight into how investors can harness retail investor sentiment using the power of big data analytics. Retail investors vastly outnumber sophisticated investors, and often only have access to general business news instead of specialized financial news. Although collectively they do not exert definitive effects on market returns in the FTSE 100, they can add noise to the market, thereby increasing volatility and potentially causing prices to temporarily deviate from their fundamental values. This is both a statistically and economically significant result, with this study demonstrating that an active trading strategy exploiting this short-term noise window outperforms a buy and hold strategy on a risk-adjusted basis. These findings reveal the potential and scope for sentiment analysis conducted using big data analytics, opening future avenues for trading strategy design. Future research could seek to replicate this analysis on multiple Australian indexes (e.g. ASX 200 and ASX 300), with there being evidence that the effects of sentiment on financial returns are stronger for stocks with lower market capitalization (Tetlock, Saar-Tsenchantsky and Macskassy, 2008). Future research could also investigate the effect of practical constraints such as transactions costs. Additionally, the effect of sentiment on volatility could potentially be exploited with an options trading strategy. Such a strategy may also prove useful for hedging purposes.

References


2. TESTING FOR PRICE BUBBLES IN AUSTRALIAN LISTED EQUITIES AND A-REIT MARKETS
TESTING FOR PRICE BUBBLES IN AUSTRALIAN LISTED EQUITIES AND A-REIT MARKETS

Abstract

Price bubbles are a phenomenon of asset markets that contradicts market efficiency. In this paper we explore the prevalence of asset-price bubbles in Australian listed industrial equities and A-REIT markets. The Australian market is a unique setting to test for price bubbles, given the regular reference to price bubbles in sections of the media and the strength of the financial sector to the overall economy. In contrast to the US stock market, we find little evidence of price bubbles in historical returns of Australian markets (1992-2016). Our article also provides the reader with a consolidated review of three leading asset price bubble detection methodologies. Our review and results can help investors better understand price dynamics and contribute to policy discussions on financial stability.

1.0 Introduction

Price bubbles are a phenomenon of financial markets, observed across time and asset classes. The concept of a price bubble is relatively easy to convey, being a rapid detachment in prices from fundamental values. However, in practice bubbles are challenging to detect ex post and arguably impossible to predict. Nevertheless, research in this area has important policy implications and a range of empirical approaches to bubble detection have emerged.

This article makes two contributions. Firstly, we consolidate and provide a review of three leading asset price bubble detection methodologies. These are the variance bounds test, first proposed by Shiller (1981), West’s (1987) two-step test, and unit root tests. Secondly, we test for evidence of price bubbles in listed Australian equities and real estate securities using the two recent specifications of the unit root test.


Bohl (2003), however, shows that the tech-bubble of the 1990’s may drive the finding of a price bubble in U.S. stock prices. This follows Diba and Grossman’s (1988) rejection of the presence of price bubbles once additional pricing factors are incorporated alongside dividends in the market fundamental pricing relation.

Evidence from more recent studies, those conducted at shorter time intervals, and for international markets is similarly inconclusive. Chung and Lee (1998) find no evidence of price bubbles in Hong Kong and Singaporean stock markets, but demonstrate a strong influence from non-fundamental factors in the pricing of Korean and Japanese stock markets. Jirasakuldech et al (2008) fail to identify a long-run relationship between prices, dividends, and earnings, taking this as evidence of price bubbles.

Using the unit root price bubble detection methodology, we test for evidence of price bubbles in Australian listed equities and REITS using the S&P/ASX 200 Index.
during the period May 1992 to April 2016. The Australian market is a unique setting to test for price bubbles, given the regular reference to price bubbles in sections of the media and the strength of the financial sector to the overall economy. Interestingly, we find no evidence of sustained deviations of prices from fundamentals that would indicate a bubble. Where our test indicates a brief detachment of prices from fundamentals, there is no explosive growth in prices as would be expected. Rather, the statistical result we achieve is attributable to a large, temporary decline in dividends. Our result is also striking as it covers several business cycles, as well as notable domestic and international stock price declines including the ‘techwreck’, the Global Financial Crisis, and the end of the recent mining boom.

Examination of the Australian market is also of interest for the ways it differs from the US market. As such, this study can provide insights to analysis of market dynamics in developed but smaller, more concentrated markets. The S&P/ASX 200 Index is comparable in coverage to the S&P500 Index in that both indices cover around 80-85% of the largest listed stocks in their respective markets and so as the main equity index benchmark. However, the average S&P/ASX 200 firm is much smaller than the average S&P 500 firm; the market capitalisation of S&P/ASX 200 companies ranges from around $400 million to over $100 billion. By comparison, the average S&P 500 market capitalisation is around $38 billion and the largest S&P500 firms reach nearly $1 trillion in market capitalisation.

There are also important differences in industry composition and dividend yield. Firms in the Financials and Materials sectors make up over 50% of the S&P/ASX 200 Index, while the largest sectors in the S&P 500 are Technology and Health Care together accounting for around 35% of the index capitalisation. Differences also exist in the REIT composition, where Australian REITs are dominated by Retail players (notably Westfield) while the US REIT market has more weighting in the Office sector. Finally, the dividend yield on ASX-listed firms is typically higher than US firms; the S&P/ASX 200 dividend yield is around 4-5%, while it sits around 1.5-1.9% for the S&P 500.

2.0 Methodologies for identifying a price bubble

In this section we review three leading price bubble detection methodologies: (i) the variance bounds test, (ii) the West (1987) two-step test, and (iii) price-dividend ratio unit root tests.

2.1 Variance bounds test

Variance bounds test evaluate market efficiency by testing whether current prices reflect the present value of a stock’s future dividend stream. Shiller (1981) shows that, under certain orthogonality assumptions, there is an upper bound on the variance of prices under market efficiency. When this upper bound value is exceeded, prices have detached from the dividend fundamental pricing expectation.

Using this method, Shiller (1981) provides one of the first attempts to identify asset-price bubbles in U.S. stock data. He empirically compares observed prices with ex-post rational prices, calculated based on the expected value of dividend payments. With perfect foresight, the ex post rational price is the present value of the sum of all future dividends. Without perfect foresight, the ex post rational price contains an error, which increases its variance. The variance of the ex post rational price should therefore be higher than the variance of observed prices.

Shiller (1981) measures the variances based on a time series of prices and dividends and therefore assumes that the price process is stationary and ergodic. If this assumption is valid, the variance bound inequality is a good test to identify asset price bubbles in data. In reality, however, we often see that prices are not stationary and are believed to follow a random walk non-stationary process. This implies that the variance of the non-stationary price process will be higher than the variance of ex post rational prices measured using dividends, which is not due to the presence of price bubbles. There are further limitations to the use of variance bounds tests in detecting price bubbles. The variance bound test can be used only based on a cross-sectional relationship, e.g. across economies but not time. We refer the reader to Gürkaynak (2008) for further discussion of the suitability of the variance bounds test for bubble detection.

2.2 West (1987) two-step test

West (1987) attempts to overcome the limitations of variance bounds tests for detecting price bubbles and proposes a different technique. He models two situations, with and without bubbles in prices. He then tests whether the two situations yield similar results. If they do, there is no bubble present in the data.
Similar to other price bubble tests, the two-stage test assumes a fundamental pricing relationship with dividends. West (1987) assumes that dividends follow an autoregressive process, which implies that the forecasting equations are stationary in either the levels or first differences of real dividends. Thus, the first step of the model is identifying the lag order of the dividend process. In the absence of a bubble, the dividend process would be observed to drive prices. West’s (1987) model allows for observed prices to reflect both this fundamental and some bubble component. The second stage of this test then involves regressing prices on the inferred fundamental price from the dividend process. If the coefficient on dividends differs from the relationship inferred by the first stage, it is taken as evidence of a price bubble. This approach is limited in that it only detects bubbles that are correlated with dividends.

2.3 Unit root tests

The unit root test has become the most widely used method for identifying price bubble in the academic literature. Unit root tests rely on identifying a stationary series. For detecting a price bubble, the series used in the standard unit root test is the ratio between prices and dividends. As such, as with the other methodologies presented, the unit root tests are defined by the non-bubble expectation that fundamental prices are derived from dividends. The appeal of this method lies in its directness of testing the price-dividend fundamental as well as its flexibility. For example, Diba and Grossman (1988) propose an adjusted unit root test that incorporates additional pricing factors. The most straightforward method for identifying a unit root is the augmented Dickey-Fuller (ADF) test. A limitation, however, to the ADF test in price bubble detection is that it treats the entire period as a single sample. As such, it can not provide useful information on start and end points of bubble periods, and may fail if multiple bubble episodes are present in the sample.

To address this limitation of the ADF test, Phillips, Wu and Yu (2011) and Phillips, Shi and Yu (2013) propose alternative rolling window adaptations of the ADF test. In the first extension, Phillips et al (2011) propose a Supremum ADF (SADF) test that estimates ADF test statistics across windows of increasing size, then calculating the Supremum of all these tests. As a more general approach still, Phillips et al (2013) propose the Generalized Supremum ADF (GSADF) test. Like the SADF test, the GSADF test runs multiple individual ADF tests on different sample windows, but allows the start point of the windows to also vary resulting in many more sub-sample periods.

A further advantage of the Phillips et al (2011) and Phillips et al (2013) methods over both the West (1987) two-step test and the variance bounds test is the ability to detect price bubbles in real time. While the earlier methodologies provide an approach for testing whether there was a price bubble episode in historical data series, the recent unit root test methodologies have greater practical application for industry participants and regulators wanting to determine if current price patterns are likely a bubble.

3.0 Data and empirical results

We employ the unit root price bubble detection methodology to test for evidence of asset price bubbles in Australian listed equities and REITS using the S&P/ASX 200 Index and the S&P/ASX 200 A-REIT Index, respectively. Our data is monthly and covers the period May 1992 to April 2016 (qualitatively similar results are obtained from a quarterly series).

3.1 Australian equities market

We first perform the SADF and GSADF tests on Australian listed equities, using the S&P/ASX 200 index as a proxy and incorporating all parameter settings as specified in Phillips et al (2011) and Phillips et al (2013), respectively. The GSADF test and corresponding price and dividend levels are presented in Figure 1. Due to space limitations, the charts for the SADF test are not presented here. These are available from the corresponding author upon request.

Our charted results indicate that there are points at which the backwards SADF test sequence exceeds the critical value sequence. This suggests the presence of bubbles in the data. Specifically, our test indicates three periods in which there is a price bubble in Australian stock prices.
• Bubble 1: between November 2008 and February 2009
• Bubble 2: between August 2009 and November 2009, and
• Bubble 3: between August 2011 and October 2011

We note that each of these periods is relatively short and represents only a small deviation of prices from dividend. We also perform the same test using quarterly series, as well as using the Phillips et al (2011) SADF test on both monthly and quarterly series. No bubbles are detected in the SADF test and all but one of the periods disappears in GSADF tests of quarterly data.

Table 1 provides the values of the Phillips et al (2011) and Phillips et al (2013) unit root test statistics used to examine whether there are any price bubbles using all the data available for the S&P/ASX 200 index. Since the values of the test statistics are lower than most of the critical values, we are unable to find support for the existence of price bubbles in Australian equity prices during our sample period.

### 3.2 Australian REIT market

We follow a similar approach to test for the existence of price bubble in Australian listed real estate securities. Figure 2 presents the plot of A-REIT index prices and dividends and Phillips et al (2011) testing. Statistical tests for monthly and quarterly tests of the A-REIT index using both the Phillips et al (2011) and Phillips et al (2013) methods are reported in Table 2.

When we analyse monthly prices, we find that there are points at which the backwards SADF sequence exceeds the critical value sequence, which suggests that there are bubbles present in the data. Based on the SADF backward-dating strategy, there is evidence of two periods when the test detects an asset-price bubble in the Australian REIT market:

• Bubble 1: between March 2010 and July 2010; and
• Bubble 2: between September 2011 and November 2011.

The first bubble period is caused by the fact that dividends decreased by less than prices. The prices did not grow between March 2010 and July 2010 but the test still detects a bubble since dividends decrease at a higher rate. The second bubble period is relatively short and is also not associated with any sharp increase in price. We therefore conclude that REIT prices are relatively stable and follow the changes of dividends, which suggests that there are no evident asset-price bubbles in REIT prices.

---

**Figure 1: S&P/ASX 200 Prices and Dividends**

Figure 1 plots the test results following the Phillips et al (2013) approach for the ASX200 equities index monthly price-dividend ratio series from May 1992 to April 2016 in panel (a) and the corresponding price and dividend levels in panel (b). Shaded areas represent regions where a price bubble is detected.
TABLE 1: S&P/ASX 200 UNIT ROOT TEST STATISTICS

Table 1 presents the results of the unit root tests conducted on monthly and quarterly data for the S&P/ASX 200 Index between May 1992 and April 2016. We use the Phillips et al (2011) method to estimate the SADF test statistic and the Phillips et al (2013) method to estimate the GSADF test statistic. Test-Stat is the test statistic for each test and CV represents critical values for the tests at relevant significance levels.

<table>
<thead>
<tr>
<th></th>
<th>Test-Stat</th>
<th>CV 90 pct</th>
<th>CV 95 pct</th>
<th>CV 99 pct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SADF</td>
<td>-0.829</td>
<td>0.306</td>
<td>0.558</td>
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<tr>
<td>GSADF</td>
<td>0.450</td>
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<tr>
<td>SADF</td>
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<tr>
<td>GSADF</td>
<td>0.992</td>
<td>0.704</td>
<td>0.981</td>
<td>1.423</td>
</tr>
</tbody>
</table>

The role of REIT dividends is particularly significant in analysing these results, as to maintain the trust structure REITs must pay out at least 90% of earnings as a distribution to shareholders, with many REITs achieving even higher earnings payout ratios through use of debt and tax deductions related to depreciation. During 2010-2011, many REITs were consolidating dividend payouts levels following ongoing correction post-GFC. However, some bucked this trend. For example, Westfield Retail Trust increased their dividend payout to 100% of earnings.

Results from the two unit root tests on all data (Table 2) confirm our hypothesis that there is little evidence of asset-price bubbles in REIT prices.

In unreported results, we perform tests for price bubbles in both the listed equities and real estate samples using the variance bounds test and West (1987) two-step test. Across all methods we find consistent empirical results that reject the presence of price bubbles. Results from these further tests are available from the corresponding author upon request.
Figure 2 plots the test results following the Phillips et al (2013) approach for the A-REIT index monthly price-dividend ratio series from May 1992 to April 2016 in panel (a) and the corresponding price and dividend levels in panel (b). Shaded areas represent regions where a price bubble is detected.

Table 2 presents the results of the unit root tests conducted on monthly and quarterly data for the S&P/ASX 200 Index between May 1992 and April 2016. We use the Phillips et al (2011) method to estimate the SADF test statistic and the Phillips et al (2013) method to estimate the GSADF test statistic. Test-Stat is the test statistic for each test and CV represents critical values for the tests at relevant significance levels.

<table>
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<tr>
<th></th>
<th>Test-Stat</th>
<th>CV 90 pct</th>
<th>CV 95 pct</th>
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<td>Monthly</td>
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</table>
Conclusion and policy implication

This article summarises some of the most commonly used methods for detecting price bubbles. We then use the most widely adopted methodology, the unit-root test, to test for evidence of price bubbles in Australian listed equities and real estate. Using the S&P/ASX 200 index as a proxy for the stock market and the S&P/ASX 200 A-REIT index as a proxy for listed real estate securities we find little evidence of price bubbles.

Following the approach of Phillips et al (2013) we find only marginal deviations from fundamental implied prices over the time period May 1992 to April 2016. We can attribute these apparent bubble episodes to decreases in dividends more than explosive growth in prices, and find no evidence in reported test statistics of price bubbles.

These results are both insightful and interesting to practitioners and regulators. Price bubbles have important implications for the investment community and our understanding of market efficiency. Regulators seeking to ensure a well-functioning market are also keen to develop methods for detecting bubbles. Given the well-known price bubbles in international markets, including the tech-wreck and global financial crisis, our findings indicate that the Australian stock market has been relatively resilient in past decades to price bubbles. Our discussion around alternative methodologies for price bubble detection, and support for the advantages of using unit root tests, hopefully can guide future research and aims to detect bubbles in real-time.

References


3. MOMENTUM IN AUSTRALIA
This study provides a description of momentum in Australia, seeking to provide a benchmark for academics and practitioners in the search to improve the performance of momentum strategies. Our findings reveal that there is a strong momentum effect within members of the S&P/ASX200 that was temporarily affected by the GFC. We also provide the first estimation of the current dollar value of momentum in Australia available to funds management.

Momentum in the Australian Market

The literature on momentum in Australia demonstrates both a significant momentum effect (see Hurn & Pavlov (2003), Demir, Muthuswamy et al (2004), Drew, Veeraraghavan et al (2004) and Bettman, Maher et al (2009)) and a non-significant momentum effect (see Griffin, Ji et al (2004), and Durand, Limkriangkrai et al (2006)). Brailsford & O’Brien (2008) and O’Brien, Brailsford et al (2010) attempt to reconcile this disparity by comparing the design empirics, sample periods, and cross-sectional stock selection used in prior studies with mixed success. This study is an attempt to provide a comprehensive description of momentum in Australia by testing momentum amongst the S&P/ASX200 constituents rather than just based on market capitalization as used in the majority of prior studies.

This study examines momentum returns using the overlapping portfolio method to create decile portfolios as per Jegadeesh & Titman (1993). Table 1 presents the mean monthly momentum returns of two momentum strategies calculated using six months of prior price data and a forward period of six months (Panel A and Panel B; for Panel B, a month has been skipped between stock ranking and portfolio formation, as is typical in prior studies). These mean monthly returns are separated into deciles, ranked from low return stocks (Loser, 1) to high return stocks (Winner, 10). The Winner Minus Loser (WML) portfolio indicates the zero cost portfolio strategy of maximizing high return stocks and minimizing low return stocks. Table 1 demonstrates the presence of a momentum effect in S&P/ASX200 stocks, with statistically significant WML returns for both portfolios. Further, the WML mean and high return (Winner) portfolio is significantly different from zero for both portfolios. Extending this analysis utilizing longer data windows of three to twenty four months, this study also confirms that momentum is a medium-term effect with decreasing returns with increasing holding periods.

It is possible that higher returns are the result of risk exposure rather than a source of abnormal return performance. CAPM adjusted returns reveal that risk is not a primary determinant, with positive, significant returns for the WML portfolio in addition to the high return (Winner) and low return (Loser) portfolios.
### TABLE 1: MOMENTUM RETURNS IN THE S&P/ASX200 UTILISING STRATEGIES 6/0/6 AND 6/1/6

<table>
<thead>
<tr>
<th>Decile</th>
<th>Panel A (6/0/6)</th>
<th>Panel B (6/1/6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>p (t-stat)</td>
</tr>
<tr>
<td>Loser</td>
<td>-0.0042</td>
<td>0.4092 (-0.8276)</td>
</tr>
<tr>
<td>2</td>
<td>0.0031</td>
<td>0.3585 (0.9208)</td>
</tr>
<tr>
<td>3</td>
<td>0.0056</td>
<td>0.0315 (2.1700) *</td>
</tr>
<tr>
<td>4</td>
<td>0.0084</td>
<td>0.0002 (3.8382) **</td>
</tr>
<tr>
<td>5</td>
<td>0.0133</td>
<td>0.0267 (2.2371) *</td>
</tr>
<tr>
<td>6</td>
<td>0.0183</td>
<td>0.0127 (2.5194) *</td>
</tr>
<tr>
<td>7</td>
<td>0.0184</td>
<td>0.0281 (2.2160) *</td>
</tr>
<tr>
<td>8</td>
<td>0.0129</td>
<td>0.0000 (4.8094) **</td>
</tr>
<tr>
<td>9</td>
<td>0.0107</td>
<td>0.0000 (5.6054) **</td>
</tr>
<tr>
<td>Winner</td>
<td>0.0150</td>
<td>0.0000 (6.6930) **</td>
</tr>
<tr>
<td>WML</td>
<td>0.0193</td>
<td>0.0001 (3.9397) **</td>
</tr>
<tr>
<td>Index (XJOA)</td>
<td>0.0079</td>
<td>0.0079</td>
</tr>
</tbody>
</table>

**Note:** Table presents the mean monthly momentum returns of a J=6, K=6 momentum strategy (both Panel A and Panel B). This study utilizes traditional Jegadeesh & Titman (1993) style notation to describe momentum returns using the J/S/K format, where J is equal to the number of months over which momentum is measured, S is the skip period (either 0 or 1), and K is the number of forward periods over which the momentum effect is measured. The 6/0/6 and 6/1/6 strategies are extensively used in the literature as representative cases for momentum portfolios. XJOA is the monthly mean return of a comparison accumulation index. Significance is denoted by * (5% level) and ** (1% level).
MOMENTUM IN AUSTRALIA - cont

Momentum and the Global Financial Crisis in Australia

During the height of the Global Financial Crisis, the ASX regulators banned short selling from the 22nd September 2008 to the 25th May 2009 (see ASX Circulars (2008) and (2009)). This study uses this interval as a proxy for the GFC period to examine the performance of momentum strategies during this difficult time. By performing regression analysis in the relevant subsamples, Table 2 shows that momentum performance was impacted during the GFC (with a statistically significant negative coefficient), but that this impact was short-lived, with momentum performance rapidly returning to pre-GFC levels after this interval.

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
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<tr>
<td>Alpha</td>
<td>0.0226</td>
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</tr>
<tr>
<td>Beta</td>
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<td>0.0000 (-4.2916) **</td>
</tr>
<tr>
<td>GFC</td>
<td>-0.2006</td>
<td>0.0000 (-23.9770) **</td>
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<tr>
<td>Post-GFC</td>
<td>-0.0016</td>
<td>0.6680 (-0.4292)</td>
</tr>
</tbody>
</table>

Note: Table presents the GFC regression results for the WML portfolio for the momentum strategy calculated using six months of prior momentum data and a forward period of six months. Significant values are marked * (5% level) and ** (1% level).

Momentum Capacity in Australia

It is particularly important to assess the maximum amount of money that could potentially be invested in momentum strategies in Australia. This is because equity analysts favour momentum stocks and equity fund managers typically have mandates that allow them to invest only in stocks within specific S&P indices. This study constructs a rolling time-series of the maximum obtainable dollar value of both expected high return and low return portfolios to estimate the upper bounds of the momentum effect in Australia, as shown in Figure 1. In order to determine a dollar value of momentum in Australia, this study utilizes the Bloomberg Fund Classifications System (2013) to identify listed funds in Australia that utilize a momentum strategy, resulting in 32 funds with a total of $1.5 billion Funds Under Management (FUM). This capacity is sufficiently substantial to be of practical significance for investment fund managers.
This study provides a comprehensive description of momentum in Australia. A key finding is the prevalence of momentum effects within the S&P/ASX200 index constituents. As membership of these indices account for liquidity and market capitalization, these results are particularly robust compared to prior studies utilizing market capitalization alone. This study also reveals that the performance of momentum strategies was temporarily affected by the GFC. In the first attempt to estimate the dollar capacity of momentum in Australia, this study also confirms the significance of momentum strategies for investment fund managers. These findings are important for academics and practitioners and are a step towards closing the gap between theory and implementation. This study also provides a benchmark for future work examining ways to improve the performance of momentum strategies. Analysis of momentum in Australia would further benefit by extending this analysis to the other large capitalization indexes in Australia, namely the S&P/ASX50 and the S&P/ASX100.
<table>
<thead>
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<th>Source</th>
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4. FORECASTING THE AUSTRALIAN YIELD CURVE
Abstract

We apply a number of forecasting models to Australian Government Bond yields. All methods rely solely on the history of yields. Consistent with findings from US Treasury data, we show that the simplest forecasting models across all maturities and forecasting horizons are generally the best: the forward yield (when available) and the random walk model. Models with more structure—e.g. principal components and Bayesian vector autoregression—can help forecast overnight yields at very short horizons, but provide little or no improvement in other cases.

Keywords: Forecasting; Term Structure; Australian Government Bonds.

1. Introduction

Prices and interest rates on government securities play a crucial role in determining, and revealing, broader financial and economic conditions. As well as directly determining government borrowing costs, the risk-free rate that investors can earn is a key component of workhorse pricing models for risky assets and derivatives. Further, borrowing costs for both households and businesses can be decomposed as the sum of the interest rate on government securities with no default risk and a credit spread that compensates investors for default risk. Accurate forecasts of these rates help both private and public agents make better decisions regarding policy, consumption, investment, savings and monetary and fiscal policy.

A broad literature investigates the performance of forecasting models for yields on US treasury securities. Equivalent evidence regarding Australian Government Bonds (AGBs) is significantly less developed. Our paper contributes to this literature by estimating and testing the out-of-sample performance of a variety of forecasting models proposed in the finance literature. Our aim is to provide robust evidence for financial market practitioners and policy makers on the comparative performance of forecasting models for AGB yields across maturities and horizons that are relatively simple to estimate and that rely only on the history of yields themselves. In this we are assuming that all relevant information for forecasting future yields is contained in the history of the cross-section of yields and are thus abstracting from macro-finance models such as Kim and Orphanides (2005) and Chernov and Mueller (2012), and “hidden factor models” such as Duffee (2011) and Joslin, Priebsch, and Singleton (2014).

We test a suite of models that vary in complexity from a simple random walk to methods using principal component analysis (PCA) and Bayesian vector autoregressions (BVARs). We evaluate the forecasting performance of each model for the zero coupon nominal yield on AGBs with overnight, one year and ten year maturities over horizons from one month to 48 months.

We report three key findings. First, while models with more structure (including VAR, PCA and BVAR methods) can outperform the random walk model for forecasting the overnight yield, these models almost never outperform the use of the forward yield as a forecast for horizons where the forward yield is available. Second, the random walk model outperforms nearly all other models for forecasting the one year yield at all forecast horizons exceeding one month. For the one month ahead forecasts of the one year yield, any gains with respect to the random walk model are marginal. Third, the random walk model is superior to all other models for forecasting the 10 year yield at forecast horizons of
under twelve months. For horizons of one year and longer, the BVAR offers some forecast performance improvement relative to the random walk model. However, the gains are small and not statistically significant according to Diebold and Mariano (1995) tests of equal forecast accuracy.

Our results support the notion that many forecasting models proposed in the literature have a hard time beating the simple no-change random walk forecast (Carriero, Kapetanios, and Marcellino, 2012). For AGBs, this is the preferred model for the vast majority of yields and forecast horizons. We do find, however, that the forward curve of yields or models that incorporate information from the term structure of yields can lead to an improvement compared with the random walk for forecasting the short-rate, and encourage practitioners to consider using these methods.

The remainder of the paper proceeds as follows. Section 2 outlines the data and methodology, Section 3 presents and discusses the results, and Section 4 concludes the paper.

2 Data and methodology

Annualised Australian Government Bond (AGB) yields were obtained from the Reserve Bank of Australia (RBA) website and cover the period July 1992 to December 2018.5

Our dataset contains end-of-month bond yields for maturities starting with the overnight rate and ending with the 10-year rate, in three-month increments. This provides us with a panel of 318 monthly observations for 41 variables. Some descriptive statistics are provided in Table 1. The average yield ranges from 4.50 percent (3 month) to 5.44 percent (10 year) and the standard deviations of yields vary from 1.71 percent (overnight) to 1.94 percent (5 and 7 year). Our sample period covers both low and high interest rate environments—the short rate varies from a minimum of 1.50 percent to 7.60 percent while the long rate varies from 1.88 percent to 10.47 percent.

The models include the random walk forecasts, forecasts based on the forward curve, univariate autoregressions (AR) using both direct and power-up methods, vector autoregressions (VAR) using both direct and power-up methods, the principal components method of Stock and Watson (2006), the principal components method of Duffee (2013) and the Bayesian vector autoregression (BVAR) proposed by Carriero, Kapetanios, and Marcellino (2012). A brief description of all of the models under evaluation are provided below, although detailed treatments of the principal components forecasting models and the BVAR method are omitted from this paper in the interest of brevity.

4. Two notable exceptions are Chen, Svec, and Peat (2016) and Faff and Treepongkaruna (2013). Chen, Svec, and Peat (2016) investigate the performance of the dynamic Nelson and Siegel (1987) model and show that, when estimated in a robust state-space framework, this model can outperform a random-walk benchmark when forecasting the term structure of AGB yields. Faff and Treepongkaruna (2013) focus on real rather than nominal yields and show that a two-factor term structure model tends to outperform a simple one-factor model for forecasting Australian real yields across a variety of term-structures.

To fix notation, let $y_t^n$ represent the continuously compounded yield for a zerocoupon bond that matures at time $t+n$ with a payoff of one dollar, and let $\hat{y}_{T+s}^m$ represent the forecast obtained for yield with maturity $n$ at horizon $t+s$ using model $m=\{\text{RW, FWD, AR, AR-D, VAR, VAR-D, SW, PCA, BVAR}\}$. For each model, $m$, yield maturity, $n$, and forecast horizon, $t+s$ with $s \in \{1, 3, 6, 9, 12, 24, 48\}$, we calculate the mean squared forecast error (MSFE) from the rolling estimation windows using:

$$MSFE_{s,n}^m = \frac{1}{N_w} \sum (\hat{y}_{T+s}^m - y_T^n)^2$$

where $N_w$ denotes the number of rolling windows for which forecasts are produced. The square root of this (RMSFE) can be interpreted as the forecast error for each model, yield and horizon measured in basis points.

We test seven models proposed in the literature. These are briefly described below.

2.1 Random walk forecasts

The random walk forecast of $y_{t+h}^n$ (denoted in our notation as $\hat{y}_{t+h}^{RW}$) is given by the current value of $y_t^n$. In other words, under this forecasting framework, the forecast of the path of future interest rates at each forecast horizon is the current interest rate:

$$\hat{y}_{t+h}^{RW} = y_t^n$$

Duffee (2002) and Diebold and Li (2006) show that the random walk forecast performs well compared with more structured alternatives. Similar to Carriero, Kapetanios, and Marcellino (2012), we use this model as a benchmark for assessing other forecasts.

2.2 Forward rate forecasts (FWD)

The expectations hypothesis asserts that the term structure of interest rates reflects market participants’ expectations of future short-term interest rates as well as term premia that are either constant or equal to zero. In the pure form, the expectations hypothesis states that the expectation of the short-rate at horizon $t+h$ is equal to the $h$-period forward short-rate at time $t$, which we denote by $f_{t,t+h}^0$ (see e.g. Friedman, 1979). Longstaff (2000) provides evidence that the pure expectations hypothesis cannot be rejected for very short forecast horizons using data on US treasury bills. As discussed in Finlay, Olivan, et al. (2012), the pure expectations hypothesis becomes theoretically less plausible as the time horizon lengthens because of the existence of various risk premia that may or may not be time-varying. Nevertheless, we test the performance of the pure expectations hypothesis for forecasting the overnight yield by constructing forecasts of the form:

$$\hat{y}_{t+h}^{\text{FWD}} = f_{t,t+h}^0.$$  \hfill (3)

The RBA data used in this study only contain the forward rates for the overnight yield. We therefore bootstrap the corresponding one year forward rate from the spot rates. Bootstraps of the 10 year forward rates would require observations of yields beyond 10 years, which are not made available in our dataset. We do not test this model for predicting yields for that maturity.

2.3 Univariate autoregressions (AR, AR-D)

Univariate autoregressive forecasts can be produced in two ways: the power-up and direct approaches. In the power-up approach, the forecasts for $h$-step ahead horizon are obtained by estimating the parameters of an AR(1) equation and then computing recursive forecasts for the $h$-step ahead forecasts as in (4). Direct forecasts are obtained by estimating a simple linear regression where the LHS variable is the $n$-period yield at time $t$ and the RHS variable is the $n$-period yield at time $t-h$. Forecasts for horizon $h$ are then obtained as in (5). As Carriero, Kapetanios, and Marcellino (2012) observes, direct forecasts optimize the $h$-step ahead mean squared forecast error, and can be more robust to misspecification than power-up forecasts. Power-up forecasts are more efficient insofar as they use more data to estimate the AR relationships. The random walk forecast can be considered a restricted version of these models where the intercept term is set to zero and the coefficient on the previous period’s yield is set to one. We provide results for both these approaches, labeling them $AR$ and $AR-D$, respectively:

$$\hat{y}_{t+h}^{AR} = \hat{\alpha} + \hat{\beta} y_{t+h-1}^n$$ \hfill (4)

$$\hat{y}_{t+h}^{AR-D} = \hat{\alpha}_n h + \hat{\beta}_n y_t^n.$$ \hfill (5)

2.4 Vector autoregressions (VAR, VAR-D)

Vector autoregression (VAR) yield forecasts analogous to the AR forecasts are obtained by regressing the vector of current yields onto the vector of yields either in the previous period, with $h$-period forecasts then
produced recursively, or onto yields \( h \)-periods ago with forecasts computed directly. The regression specifications are as per (6) for the power-up approach and (7) for the direct approach:

\[
\hat{Y}_{t+h}^{VAR} = \hat{A}_h + \hat{B}Y_{t+h-1}^{VAR}
\]

where \( Y_t \) is the \( p \times 1 \) vector of yields across all maturities in period \( t \), \( A \) and \( Ah \) are \( p \times 1 \) vectors of intercepts, and \( B \) and \( Bh \) are \( p \times p \) matrices of coefficients. The regression specifications in (6) and (7) are the vectorized analogs to (4) and (5), which represent univariate autoregressions. Equations (4) and (5) can be considered restricted versions of Equations (6) and (7) where the non-diagonal elements of \( B \) and \( Bh \) are set to zero. One drawback of the VAR approach is that the number of parameters to be estimated increases with the square of the number of included yields. This can lead to parameter instability or, in the limit, parameter non-identification as \( p \) increases.

2.5 Principal Components (PCA)

A common yield forecasting approach relies on compressing the information contained in the cross-section of yields into a lower dimensional vector, for example using principal component analysis Duffee (2013). Following Litterman and Scheinkman (1991) a very well-established result in the term structure literature is that the first three principal components of the term structure capture nearly all of the variation in yields across the curve.

The factor loadings associated with these principal components lend themselves to the following interpretations: the first principal component shifts the level of all yields across the curve (commonly referred to as "level"); the second principal component shifts the short-end and the long-end in opposite directions (commonly referred to as "slope"); and the third principal component moves the short-end and the long-end of the curve in the same direction, but away from the intermediate maturities (commonly referred to as "curvature"). Figure 1 shows the loadings of yields on their first three principal components.6 This figure is analogous to Figure 7.2 in Duffee (2013) which presents these loadings for the US treasury yield curve.

Following Duffee (2011, 2013), the three principal components are estimated from the history of the term structure and are then forecasted using a VAR(1) framework. To construct forecasts of the yields themselves, projections of yields onto the principal components is done via OLS and these parameters are used to map the forecasts of the principal components back to yields.

2.6 Stock and Watson (2006) principal components (SW)

Another methodology for forecasting with principal components of the term structure is the Stock and Watson (2006) framework. Stock and Watson (2006) advocate the following procedure for forecasting a yield with a given maturity (say the short-rate). First, the principal components are calculated using the history of the term structure excluding the yield that is being forecasted. Second, for each forecast period, \( h \), the history of the yield to be forecasted is projected onto this factor lagged by \( h \) periods and its own lag from \( h \) periods ago via OLS. The parameters from this regression are used to forecast the yield \( h \) periods ahead using the current value of the yields and factors.

In this sense, the Stock and Watson (2006) framework can be thought of as a direct projection analog of the power-up method of Duffee (2013), although the methods differ in how they incorporate information in the own-lags of the yield being forecasted.

2.7 Carriero, Kapetanios, and Marcellino (2012) Bayesian VAR (BVAR)

Carriero, Kapetanios, and Marcellino (2012) propose dealing with the overparameterization problem of VAR...
models with Bayesian methods. Their model uses a large Bayesian VAR (BVAR) with an optimal amount of shrinkage towards univariate AR models with high persistence. Carriero, Kapetanios, and Marcellino (2012) show that the BVAR approach outperforms the random walk forecast for US treasury yields across a range of maturities and forecast horizons, although the gain over the random walk is small.

3

Empirical results

The root mean squared forecast errors (RMSFEs) estimated for the overnight yield using our rolling estimation and forecast windows are shown in Panel A of Table 2. Each row of Table 2 corresponds to a separate forecast horizon (from one month to 48 months). Each column corresponds to one of the nine models discussed in Section 2. A value of 0.19 in the first row (one month forecast horizon) and third column (random walk model) of Panel A of Table 2 indicates that the root mean square of the forecast error for the overnight yield one month from now using the random walk forecasts was approximately 19 basis points.

Panel A of Table 2 indicates that although models with more structure do outperform the simple random walk model for forecasting the overnight yield at all horizons shorter than 24 months, the forward yield is usually the best predictor. One-sided Diebold and Mariano (1995) tests for equal forecast accuracy between each model and the random walk benchmark only reject the null of equal forecast accuracy at the 5% level for the Stock and Watson (2006) model and the BVAR forecasts at the one month horizon. There is some weak evidence that forecasts from the VAR model outperform the random walk benchmark at that horizon and that the forward rate forecasts are more accurate than the random walk forecasts at the six and nine month horizons.

TABLE 2

<table>
<thead>
<tr>
<th>Horizon</th>
<th>RW</th>
<th>FWD</th>
<th>AR</th>
<th>AR-D</th>
<th>VAR</th>
<th>VAR-D</th>
<th>SW</th>
<th>PCA</th>
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<tr>
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<td>1.55</td>
<td>1.56</td>
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<tr>
<td>48</td>
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<td>2.22</td>
<td>2.13</td>
<td>2.13</td>
<td>2.02</td>
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</table>
Panels B and C of Tables 2 present corresponding forecast performance for one-year and ten-year bonds. Panel B shows that the random walk forecast is either the best predictor of one-year yields, or very close to it, across all forecasting horizons. Panel C shows that essentially the same conclusions can be extended to the ten-year yield, although the BVAR offers mild improvements over the random walk at long forecasting horizons.

### Table 2: RMSEs for Forecasted 10-Year Yields

<table>
<thead>
<tr>
<th>Horizon</th>
<th>RW</th>
<th>FWD</th>
<th>AR</th>
<th>AR-D</th>
<th>VAR</th>
<th>VAR-D</th>
<th>SW</th>
<th>PCA</th>
<th>BVAR</th>
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<tr>
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<td>0.46</td>
<td>0.53</td>
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<td>6</td>
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<td>0.74</td>
<td>0.70</td>
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<tr>
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<td>1.08</td>
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<tr>
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### References


In this paper we have applied a number of forecasting models to AGB yields over a range of forecasting horizons. These models vary from the simple—random walk and forward yield—to the computationally intensive—PCA and BVAR. Overall, and consistent with findings from US Treasury data, we show that the forward yield is the best predictor when it is available. When the forward yield is not available, the random walk is, or is at least statistically indistinguishable from, the best predictor in all cases other than when forecasting the overnight yield at the one month horizon.


5.

BITCOIN A BIT UNREGULATED?
BITCOIN A BIT UNREGULATED?

Abstract

This paper reviews and contrasts the regulatory regime governing cryptocurrencies in Australia with those of the United States and European Union where the use of cryptocurrencies in general and bitcoin in particular, is gaining momentum. This comparative analysis led the authors to conclude that the Australian regulatory regimes are comparable, especially in relation to anti-money laundering activities. The finding cements the argument that it is timely to have a streamlined classification of bitcoin and/or cryptocurrencies across the jurisdictions, to provide the necessary guidance for all the stakeholders in the financial system.

1. Introduction

Cryptocurrencies are a protocol, which has garnered prominence as a substitute to the fiat payment system in recent times. The need for reduced transaction costs, greater transparency and accessibility makes cryptocurrency a favoured instrument of payment. Various researchers have explored, inter alia, the suitability of, and the challenges posed by this virtual payment system; counter-terrorism finance; and taxation issues.

Bitcoin helps investment banks perform two important tasks: know your customer, and anti-money laundering (AML) checks. This is possible with blockchain. According to the 2016 Goldman Sachs report (Schneider, 2016), investment banks save approximately USD6 billion per year by using blockchain. It added that blockchain ensured efficient equity market through the shrinking of post-trade settlement and clearing processes. However, bitcoin is not always a boon for the finance industry nor the economy overall. Foley et al. (2019) finds that approximately one-half of the bitcoin transactions are associated with illegal activities. Bitcoin users can mask their identities by using mixing services to bounce bitcoins between various addresses and recombine them in a bitcoin wallet hosted on the dark web known as Silk Road (Böhme et al., 2015). The Silk Road historically was a marketplace for drug dealers, gunrunners and document forgers. The magnitude of activity that takes place in these webs can be gauged through the FBI seizure of over USD4 million bitcoin in 2013 (Foley et al., 2019). The correlation of bitcoin’s market value and its use in illegal activities clearly indicate that formalized regulation is becoming increasingly urgent.

Research on the need to have uniformed understanding of cryptocurrencies and legislative intervention for a more systematic and transparent governance is limited. Interestingly, the authors noted that none of the selected jurisdictions had any legislations specifically on bitcoins or cryptocurrency. Hence, this research is timely; the current situation across jurisdictions must be analysed along with its regulatory complexities identified. Through normative analysis, the authors investigated the current definition and governance of cryptocurrencies generally in Australia, the United States and the European Union. The analysis led to the conclusion that there was a prevalent reluctance to define cryptocurrencies and take legislative measures. Where effort has been evident, it was inconsistent. Hence, the authors propose a framework of self-regulation that makes cryptocurrency a safer alternative in the retail market without undermining its advantages.

2. Cryptocurrencies

Cryptocurrencies, are protocols that allow for the validation of transactions without the use of third party intermediaries like banks, credit card providers, escrow agents or recording agencies (Marian, 2015-2016). Bitcoin, a peer-to-peer electronic cash system was one of the first forms of crypto-
currency created by an unknown person or group of persons under the pseudonym Satoshi Nakamoto in 2009 (Marian, 2015-2016, Pittman, 2016, Godsiff, 2015, Turpin, 2014, Pacy, Fall 2014, Jeans, 2015, Hewitt, Winter 2016, McLeod, 2017, Tu and Meredith, 2015, Litwack, 2015). This system dramatically reduced transaction costs related to value transfers (Turpin, 2014, Litwack, 2015); facilitated financial transactions for those unable to access traditional banking systems (McLeod, 2017); and circumvented the drawbacks of managed or commodity based systems by enabling the formation of self-regulating smart contracts independent of the involvement of traditional banks, solicitors or accountants (Marian, 2015-2016, Bacina, 2017). Put simply, it is a completely decentralized financial payment system (Pittman, 2016, Godsiff, 2015, Jeans, 2015).

 Bitcoins are created through a process called mining, where miners solve complex algorithms and record it as a community-validated secure virtual ledger known as ‘blockchain’ (Godsiff, 2015, Pacy, Fall 2014, Jeans, 2015, Hewitt, Winter 2016, Marshall, 2015, Gamble, 2017, McLeod, 2017, Tu and Meredith, 2015). Although the protocol does not impose any restrictions on the number of miners who want to be involved in this process, computer processing capacity and electricity costs may be limiting factors (Marshall, 2015).

The difficulty of the mining process prevents duplication, which thwarts double-spending problems and fraud in decentralized currencies (Pittman, 2016, Godsiff, 2015, Turpin, 2014, Pacy, Fall 2014, Tu and Meredith, 2015). Hence, as a strictly virtual technological innovation, bitcoin, poses a challenge to centralized currencies and payment systems of states and corporations (Godsiff, 2015).

As of January 2018, mined bitcoins stood at 16.8 million (Zuckerman, 2018) with 4.2 million remaining to achieve its supply cap of 21 million (Zuckerman, 2018, Marshall, 2015). Some believe that increased algorithmic complexity would slow miners and thereby impede growth, but this is unlikely to happen (Marshall, 2015, Abramovich, 2014). The cap is premised on the notion of scarcity which increases the value of bitcoins (Zuckerman, 2018).

3. The Australian Position

Anti-money laundering law

In Australia, the primary legislation for money laundering and terrorism financing is the Anti-Money Laundering and Counter-Terrorism Financing Act 2006 (Cth)(AML/CTF) which was amended in 2017. It repealed the definition of e-currency and introduced digital currency, which extends to bitcoin. Section 5 defines digital currency to include: medium of exchange, a store of economic value, or unit of account and not issued by a government body and used interchangeably as consideration for goods and services and is readily available to the public or has been declared as a digital currency by the AML/CTF rules.

This amendment was dramatic given that in 2014, the Australian Transactions and Reporting Analysis Centre (AUSTRAC) CEO was against regulation as the volatility and insecurity of cryptocurrencies was deemed to hinder mainstream usage of these form of currencies (Marshall, 2015). Within three years, the Australian government changed its stance as reports from the global watchdog Financial Action TaskForce (FATF) identified major deficiencies in Australian AML laws (Reuters, 2018, Lee, 2014). The report acknowledged bitcoin’s legitimate uses and recommended the introduction of strict regimes to combat the funding of domestic and international terrorism (Gamble, 2017).

As of April 2018, all digital currency exchange providers in Australia are required to register their operations with AUSTRAC (Reuters, 2018, Allman, 2018). This measure furthers its first stage of reform implementation, which aim to strengthen AML laws in Australia. The action was initiated following the lawsuit against the Commonwealth Bank of Australia for breaching AML laws (Reuters, 2018). The AML laws provide that all entities involved in the transmission of physical or cryptocurrency are required to obtain information to establish the identity of the user, monitor transactions and report suspicious or cash transactions above AUD10,000 (Reuters, 2018).
Initial Coin Offers (ICO)

The Australian Securities and Investment Commission (ASIC) recognised cryptocurrency as a legitimate form of currency in a guideline published in September 2017 (Allman, 2018). The guideline stated that the regulation applicable to crypto-asset and ICO is dependent on whether it is a financial instrument or otherwise (ASIC, 2018). It provided guidance on when the Corporations Act 2001 (Cth) is applicable and stressed that labels ascribed to a token or crypto-asset do not necessarily mean it is a financial product. Guidance was also given on when it may be considered a managed investment scheme, offer of shares, offer of derivatives, or a non-cash payment facility; and when a crypto-asset trading platform becomes a financial market (ASIC, 2018).

Taxation

The Australian Tax Office (ATO) considers bitcoin as property or asset and not currency, its supply is not a financial supply for the purposes of goods and services tax (GST) (Litwack, 2015). If it is used for personal consumption of goods and services it will not attract income tax or GST implications (Litwack, 2015). Conversely, if a business entity accepts bitcoin as payment for goods and services, it must tabulate and record the bitcoin’s fair market value equivalent of Australian currency and GST to be paid for those transactions (Litwack, 2015). For capital gains tax purposes, bitcoin is an “intangible asset” and subject to tax (Gamble, 2017, Abramovich, 2014, Litwack, 2015).

Payment Systems

The broad definition of payment systems adopted by the Reserve Bank of Australia (RBA), allows for the inclusion of cryptocurrencies. A payment system includes payment made or funds transferred in the form of cash to any sophisticated mechanisms on the Internet. The Payment Systems (Regulation) Act 1998 (Cth) defines a payment system as a ‘funds transfer system that facilitates the circulation of money and includes any instruments and procedures related to the system’. Bitcoin concerns the circulation of money, therefore it is argued to fall within the definition (Marshall, 2015).

4. REGULATING BITCOIN OR CRYPTOCURRENCY IN OTHER JURISDICTIONS

Anti-money laundering Laws

In 2013, the United States Financial Crimes Enforcement Department (FinCen) issued guidance on the applicability of the Bank Secrecy Act 1970, in relation to open and hybrid system of virtual currencies, which included bitcoin. For AML activities, bitcoin is a currency (Marshall, 2015). The FinCen regulations are not applicable where users or miners purchase physical or virtual goods or services with bitcoins. Regulations apply where administrators or exchanges accept and transmit bitcoin, or buy or sell bitcoin; and where miners sell mined bitcoin to another for real currency or its equivalent (Marshall, 2015).

The US Department of Treasury regulates financial intermediaries through FinCen. Accordingly, cryptocurrency service providers are money receivers under the Bank Secrecy Act and need to register with FinCen (Jeans, 2015, Hewitt, Winter 2016, Brito et al., 2014, Marshall, 2015). Further, the Internal Revenue Service (IRS) requires certain cryptocurrency providers to provide information and reveal the identity of their service recipients. In 2014, the New York State Department of Financial Services proposed rules requiring registration and licensing of certain cryptocurrency financial service providers (Marian, 2015-2016, Brito et al., 2014, Gamble, 2017, Descôteaux, 2014, Jackson, 2018a, Litwack, 2015). Presently, 49 states in the US require money transmitters to obtain licensing to operate (Marshall, 2015, Brito et al., 2014, Gamble, 2017). However, the impetus for state and federal regulations differ, the former aims to enhance consumer protection whereas the latter is in pursuance of AML perpetrators (Marshall, 2015).

Initial Coin Offers

The US does not consider bitcoin as securities since the definition of securities includes any note, stock, transferable share or investment contracts and it also excludes currencies (Pacy, Fall 2014, Turpin, 2014), though curiously it provides a high number of investment opportunities (Turpin, 2014).
One such investment opportunity arises from ICO which is a fundraising exercise where investors are offered new cryptocurrency in exchange for their financial backing (Lai, 2018). At present, there are only two guidelines available on ICOs, which are the Swiss and US approaches. The former outlines three types of tokens: coins issued through an ICO on a different blockchain to bitcoin; payment tokens without further functions or links to other development projects (not treated as security); and utility tokens which provides digital access to an application or service (considered as security) (Jackson, 2018b).

The US approach is mixed; if a token is used as a payment method, it will be considered as a security, in which case it has to be filed for registration with the Securities and Exchange Commission (SEC) and if used as commodity, be within the purview of the Commodities Futures Trading Commission (Jackson, 2018b). The SEC uses the Howey Test to determine whether the transaction qualifies as “investment contract”. It comprises four questions: is it an investment of money or assets? Is the investment in a common enterprise? Is there a reasonable expectation of profits? Is it reliant on the efforts of a promoter or others? (Croce, 2018). Accordingly, a recent research indicated that ICOs do not qualify as a security as it is considered “utility tokens” which means it gives access to particular online platforms or services and if purchasers are motivated by this utility function, it does not qualify as security under the Howey Test (Croce, 2018).

**Taxation**

In the US, bitcoin has varied classification. In 2013, the US District Court in the case of Securities and Exchange Commission v Trendon T. Shavers and Bitcoin Savings and Trust, Civil Action No. 4:13-CV-416 (2013) ruled that bitcoin was a currency (Turpin, 2014, Brito et al., 2014, McLeod, 2017). It is classified as asset for taxation purposes (Godsiff, 2015, Jeans, 2015, Hewitt, Winter 2016, Gamble, 2017, Descôteaux, 2014). In 2014, the US IRS Department issued guidance on taxation of cryptocurrencies. Through Notice 2014-21, it stated that cryptocurrencies were property and mined coins were to be taxed as self-employment income (Pittman, 2016). However, the challenge in the taxation of cryptocurrency was the determination of the value to be taxed given its high anonymity and price volatility (Pittman, 2016).

**Payment Systems**

There has been acknowledgment, in recent years, of the discrepancy between emphases on AML/Tax regulations and the complete sideling of the necessity to legislate on virtual payment systems (Marshall, 2015). In the US, the Electronic Fund Transfer Act 1978, was established to deal with the rights and obligations of customers and financial institutions with regards to electronic fund transfers, and this Act does not cover transactions involving cryptocurrencies (Marshall, 2015). However, in limited circumstances the Act may apply where transfers are undertaken through intermediaries that hold accounts on behalf of its users (Marshall, 2015). Despite its prevalent usage, regulators have yet to give significant consideration to the policing of cryptocurrency as a payment mode (Marshall, 2015).

The European Union (EU) which provides protection for mobile payment via its Payment Services Directive and E-money Directive has curiously, not included payments with bitcoin (Godsiff, 2015). Recently the European Central Bank (ECB) declared that the regulation of cryptocurrency is beyond its mandate (Jackson, 2018b). Although European regulators have been quick to point out that cryptocurrency investments are unwise, a dearth of guidance has been given in relation to the same (Jackson, 2018b).

There are varied approaches within the EU member states. For instance Germany, considers bitcoin private money and a financial instrument (Jeans, 2015, Descôteaux, 2014, Litwack, 2015). It is a unit of account and not ‘e-money’. German legislation, defines ‘e-money’ as the ‘digital equivalent of cash’. This clearly indicates that Germany does not consider bitcoins as currency. Hence, it is subjected to capital gains tax if the units are held for less than one year (Litwack, 2015). Denmark, on the other hand, does not consider it an asset nor currency. Finland treats it as an asset and subjects it to gains tax (Reuters, 2017) and if used as a payment for goods or services, it would be treated as trade, and any increment in the currency’s value is subject to tax (Litwack, 2015). Sweden considers bitcoin a capital investment object for tax purposes which subjects it to capital gains tax under Chapter 52 Swedish Income Act (Litwack, 2015). The Netherlands does not consider it as legal tender nor electronic money; and France, does not recognise it as legitimate currency (Abramovich, 2014).
5. ANALYSIS

The argument to keep cryptocurrencies especially bitcoins unregulated is impractical and against public interest. An unregulated platform is more vulnerable to abuse and misuse, inter alia, untraceable black market transactions and tax evasion. Regulation is clearly necessary and drawing a delicate balance between encouraging the growth of such alternative payment systems and public interest is crucial.

The first step in regulating cryptocurrency, which will involve all participants within the system, is to review the scheme itself including its protocols, procedures and rules of operation. Second, the operating regulations and rules affecting market participants need streamlining. Third, rules need to be introduced to the users of the system and service providers (Leckow, 2016).

Fiat payment systems rely on the element of trust, for instance where a bank honours a payment instruction. The main argument against cryptocurrency is the lack of the “trust” element given its non-reliance on intermediaries (Angel and McCabe, 2015, Lawler, 2018). And the counter-argument is that, this anomaly is the very reason that makes bitcoin an attractive alternative mode of payment (Angel and McCabe, 2015, Lawler, 2018). Whilst it is acknowledged that public digital ledgers are new, the need to move to private currency is not a new notion (Lawler, 2018). In fact, Nobel Prize winner Professor Hayek reasoned that private banks were given the liberty to issue currency to ensure those banks worked towards ensuring the stability of its currency (Lawler, 2018). Cryptocurrencies disconnect banks and currencies, making it possible for individuals to transact directly without the need for a financial institution facilitating the payment. To govern this position while ensuring the platform remains attractive is a challenge for the legislative community.

The general observation from the analysis of regulatory regimes in the identified jurisdictions is a stark lack of attempt to define bitcoins. The question that needs to be clearly answered is whether it is a currency, commodity, security, payment system or something else entirely (Litwack, 2015). This inability to give a determinative definition makes it challenging for legislators. According to Litwack (2015), classifying bitcoin as both currency and investment as seen in Germany may assist in facing some of the definitional challenges.

As bitcoin lacks the backing of the government similar to a fiat currency, it cannot be a currency and this is the common approach taken by the majority of the nations. Hence, the common undertaking has been to refrain from considering it as a currency. This argument is not completely valid. In fact, innovation and disruption in the technology of money is not unheard of. To be a currency, the protocol must be able to perform three functions i.e. be a medium of exchange; store of value; and unit of account. The question therefore, is whether bitcoin is able to perform these three functions. Money has evolved from shells, grain, metal and gold to government backed banknotes, digital money may very well be the next way forward. The biggest obstacle for bitcoin is the function of storage of value. Both gold and bitcoin are reliant on Mother Nature and mathematical algorithms, respectively, as opposed to fiat currency, which has government backing. Bitcoin supply is fixed, whereas fiat mode of payment can be adjusted to deal with recession and inflation (Kiviat, 2015).

Few countries have considered bitcoin as security although it is beginning to garner prominence as one. The narrow definition of security, which is to be backed by an organisation does not qualify bitcoin as a security by any measure. In the US as highlighted above, it will not be able to pass the Howey Test to be a security. Classifying bitcoins as security unlocks plethora of disclosure requirements. Even classifying it as a commodity will subject it to a criticism similar to considering it as security. Users would need to record the prices paid for bitcoins, which inhibits usage. The dual classification of currency and investment or asset provides flexibility concerning taxation and regulates it differently. The inability to understand the protocol makes it difficult to delineate and govern. Hence, most jurisdictions have taken the easy path of regulating this protocol on a needs basis, which moves it, further away from consistent classification. For example, the classification of a currency or asset is not determined by the area of law governing it. However, this protocol seems to be changing its avatar between the areas of law governing it, creating confusion for regulators due to their inability to reconcile the different approaches. This confusion on whether it be treated as a financial instrument has serious repercussions in the financial industry and requires prompt action from the regulators. In order to overcome this lack of regulatory regime, the authors recommend that the cryptocurrency industry be self-regulated. The industry will be better off developing its own standards to be complied voluntarily by all involved. These standards need formalisation and the model of self-regulation may be the subject of regulatory oversight.
The authors also recommend the classification of bitcoins and cryptocurrencies as both currency and investment, regulated by a common voluntary standard with minimal intervention from governing bodies to retain its unique advantages in being free from intermediaries. This recommendation addresses the need to recognise this increasingly fast growing medium of payment, which the public use and thus, the protection afforded, must be more than mere guidelines. Financial consumer protection is another area that needs consideration besides money laundering and taxation matters.

6. CONCLUSION

The discussion undertaken in this paper clearly indicates that the regulatory regimes on cryptocurrency in the identified jurisdictions are far from satisfactory. Whilst the Australian regulatory bodies regulate bitcoin and cryptocurrencies in general, it is a balancing act between regulating and encouraging the growth of alternative payment systems. There is sufficient predictive analysis to support the exponential growth of cryptocurrency; therefore, the onus is on regulatory bodies to achieve a consensus on the classification and implementation instruments to regulate bitcoin and cryptocurrencies.