Does the Short Rate Predict Market Returns?

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ABSTRACT
A negative relationship between short-term interest rates and equity returns is well documented. Prior research suggests that the predictive ability of the lagged short rate is economically significant. In this paper, we investigate the performance of a trading strategy under which funds are allocated to equities or fixed income according to the forecasts from predictive model that utilises the information content of the lagged interest rate. Unlike prior findings in US markets, we find no conclusive evidence that lagged interest rates have economically significant predictive ability.

INTRODUCTION
The issue of return predictability continues to attract enormous interest from both academics and industry. Since the 1960s, academics have studied predictability with a view to testing the efficient markets hypothesis (EMH). In brief, the EMH states that security prices fully reflect all publicly-available information. Equivalently, market efficiency implies that asset returns are not predictable using past returns and/or other conditioning variables.

Over time, a vast empirical literature has emerged documenting the apparent existence of predictive relationships.1 Arguably, the evidence of predictability is now too strong to dismiss. At the same time, finance theory has progressed. In light of multi-period asset pricing models, it is now well-accepted that returns will be partially predictable in an efficient market.2

From a practical perspective, investment professionals are perhaps less concerned with theoretical finance models and more concerned with understanding the predictive relationships that exist and utilising them to enhance performance. While academic research often focuses on statistical inference from predictive regressions, applied research is concerned with economic significance – does the existing level of predictability translate into economically important outcomes?

An interesting study in this vein is Breen, Glosten and Jagannathan (BGJ) (1989). BGJ note the well-documented negative relationship between US stock returns and short-term interest rates.3 They then investigate whether this relationship can be utilised to formulate a trading strategy capable of outperforming a passive buy-and-hold investment in the market. The primary finding of BGJ is that their trading strategy generates returns marginally higher than the buy-and-hold market, but importantly, with significantly lower risk. They conclude that knowledge and use of this predictive relationship is worth an annual management fee of around 2 per cent of the value of assets managed.

The idea and methodology of BGJ is simple in the extreme. The results, nonetheless, are seemingly impressive. In this paper, we investigate the economic significance of the negative relationship between short-term interest rates and Australian market returns. We employ a simple predictive model that utilises the information content of lagged interest rates to generate one-month-ahead forecasts of the market return. Based on model predictions, a trading strategy is deployed to allocate funds to equities or fixed income. The degree of predictability is judged by comparing the performance of the trading strategy to a passive investment in the

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1 See Fama 1991 for an extensive review.
2 Cochrane (1999) provides an excellent (and readable) overview of these ideas.
3 See, for example, Fama and Schwert (1977), Fama (1981), BGJ (1989) and Fama (1990).
Sections

Section 1
DATA AND METHODOLOGY

The data employed in this study are drawn from a variety of sources. The proxy chosen for the short-term interest rate is the yield on 13-week Treasury notes available from the Reserve Bank of Australia (www.rba.gov.au). Monthly holding period returns are calculated for these Treasury notes. The accumulation series for the value-weighted Australian All Ordinaries Index (AOI) is obtained from the Australian Stock Exchange (www.asx.com.au). Monthly returns are calculated using end-of-month AOI levels. All data are monthly for the period December 1976 through December 2002 (313 observations).

With a view towards comparability of results, the adopted methodology closely follows BGJ. The basic idea is as follows. At a given point in time, the one-month-ahead market return (in excess of the short rate) is forecasted using a predictive regression adopting the current short-term interest rate as the sole explanatory variable. If the prediction of excess market return is positive, the portfolio manager invests 100 per cent of funds in equities. Conversely, if the prediction is negative, the fund manager exits equities and invests in fixed income. Rolling forward one month, a new predictive regression is estimated and the process is repeated. Over an extended period of time, this process represents a trading strategy whereby funds are switched in and out of equities according to the signals from the predictive model.

Let $r_{it}$ and $d_{it}$ denote the monthly return on the market index and short rate respectively. The excess market return is calculated as $y_t = r_{it} - r_{ft}$. At a given point in time $t$, we estimate the predictive model using the ordinary least squares technique:

$$y_t = \beta_0 + \beta_1 r_{t-1} + \epsilon_t,$$

(1)

where $\epsilon_t$ is the error term for the regression. The regression estimates ($\beta_0$ and $\beta_1$) along with the time $t$ value for $f$ produce the time $t + 1$ forecast of excess market return $y_{t+1}$. Note that we follow BGJ in using a rolling estimation window. The regression is fitted using the most-recent 36 monthly observations of $y$ and of.

This approach is favoured when it is possible that the predictive relationship changes over time, hence the most-recent data may be more relevant. Arguments can also be made to utilise all historical data available, but again our methodological choices are designed for consistency with BGJ.

Implementation of the trading strategy proceeds as follows. The first estimation of model (1) uses the 36-month data sample covering January 1977 through December 1979. The regression estimates are used to forecast the excess market return in January 1980. If, for example, an up market is signaled, funds are placed into the value-weighted AOI. In calculating the realized return on this investment, we skip one day when calculating the January 1980 return (that is, we calculate the January 1980 return from 2 January through 1st February). This ensures that the trading strategy is genuinely implementable. For this exercise, daily observations on the AOI are available from DataStream starting January 1980.

Section 2
RESULTS AND DISCUSSION

The first and last one-month-ahead predictions are for January 1980 and December 2002 respectively, giving 276 predictions in total. Table 1 documents the forecasting accuracy of the predictive model. Model (1) correctly forecasts 125 of the 157 up markets ($pu = 79.62$ per cent accuracy) but only 34 of the 119 down markets ($pd = 28.57$ per cent). The overall success rate of the predictive model is 57.61 per cent (159 correct predictions out of 276).

This predictive accuracy can be judged statistically using a test developed by Henrikson and Merton (HM) (1981). HM's test of market-timing ability is based on the premise that, in the absence of predictive ability, we would expect to correctly forecast 50 per cent of up markets and 50 per cent of down markets (that is, $pu + pd = 1$). In contrast, perfect forecasting requires $pu + pd = 2$. Thus, the extent to which $pu + pd > 1$ is a measure of market-timing ability. In relation to table 1, the value of the HM test statistic is 1.0819, with a $p$-value of 0.076. Therefore, at a 10 per cent level of significance, we can conclude that the forecasting accuracy reported in table 1 is unlikely to be due to chance.

<table>
<thead>
<tr>
<th>Forecasted up market</th>
<th>Actual up market</th>
<th>Forecasts down market</th>
<th>Actual down market</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecasted up market</td>
<td>125</td>
<td>32</td>
<td>86</td>
<td></td>
</tr>
<tr>
<td>Forecasted down market</td>
<td>34</td>
<td>210</td>
<td>66</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>157</td>
<td>119</td>
<td>276</td>
<td></td>
</tr>
</tbody>
</table>
returns roughly the same as the buy-and-hold market, but with notably lower standard deviation. The same cannot be said here. While our trading strategy has lower risk, the switching portfolio is outperformed by the buy-and-hold market. Combining the mean and standard deviation measures, the switching strategy’s Sharpe ratio is also inferior to the buy-and-hold market.

Note that BGJ’s finding that the trading strategy has lower risk than the passive market investment is not surprising per se — this is an inevitable consequence of funds spending some time in the market and some time in (relatively low risk) fixed income. The significant finding is that the average return on their trading strategy matched the buy-and-hold market despite spending some time in fixed income. Similarly, the current finding that the risk of the trading strategy is lower than the passive investment is inconsequential — the fact that the trading strategy could not match the buy-and-hold portfolio is evidence against predictability.

**TABLE 2: PERFORMANCE OF BUY-AND-HOLD PORTFOLIO VERSUS TRADING STRATEGY**

This table reports summary statistics capturing the performance of two investment strategies. The first strategy is a buy-and-hold investment in the Australian All Ordinaries Index. The second strategy involves funds being switched between equities and fixed income according to the predictive model (1). The period of analysis is January 1980 through December 2002 (276 months). The Terminal Wealth figure is the December 2002 accumulated value of $1 invested under each strategy in January 1980.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean Deviation</th>
<th>Sharpe Ratio</th>
<th>Terminal Wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market portfolio</td>
<td>1.1509</td>
<td>5.38</td>
<td>$15.35</td>
</tr>
<tr>
<td>Treasury notes</td>
<td>0.7729</td>
<td>0.37</td>
<td>$8.36</td>
</tr>
<tr>
<td>Excess return on market</td>
<td>0.3780</td>
<td>5.34</td>
<td>0.0708</td>
</tr>
<tr>
<td>Excess return on strategy</td>
<td>0.3123</td>
<td>4.53</td>
<td>0.0869</td>
</tr>
</tbody>
</table>

Figure 1 displays a time-series plot of the cumulative wealth generated by the alternate approaches. Under the buy-and-hold market investment, $1 invested in the All Ordinaries Index in January 1980 grows to $15.35 by December 2002. Under the switching strategy, $1 is invested in the market in January 1980, after which accumulated funds are transferred in and out of the market according to the signals generated by the predictive model. By December 2002, the switching portfolio has grown to only $14.24.

Note from Table 1 that the trading strategy spends the majority of the sample period in equities (210 out of 276 months). To a large extent, therefore, the accumulated wealth under the trading strategy mirrors that of the passive buy-and-hold market. For the trading strategy to outperform the passive investment, the predictive model must have some ability to forecast both down markets (and hence direct funds into fixed income) and up markets (and hence direct funds back into equities if they are not already there).

Figure 1 shows that the trading strategy led the passive portfolio for most of the 1980s and 1990s. Closer examination reveals that the superiority of the trading strategy over this period is attributable to a handful of observations where the predictive model correctly forecasts a down market and directs the fund manager out of equities and into fixed income. Such occurrences can be seen around 1982-1983 and 1990-1991, where the accumulated wealth under the trading strategy grows at a linear rate. The downfall of the trading strategy can be traced to a handful of months in 2000 and 2001, where down markets were predicted (hence prompting the fund manager into fixed income), yet strong market returns eventuated in the following month.

In a study of predictability, the sensitivity of overall results to a handful of observations is a concern. In the current paper, we find little evidence of economically-meaningful predictability, but if we had, the potential sensitivity of results would be an issue. Certainly, BGJ present no such analysis. We are likely to have greater confidence in predictability findings if results are not driven by a handful of observations.

**Section 3: CONCLUSIONS**

The empirical literature on return predictability is voluminous and the weight of evidence favours a predictable component to asset returns. This paper explores the predictive power of lagged interest rates for Australian equities. In contrast to the findings of BGJ (1989) for the US market, there is little evidence that the Australian short rate predicts the one-month-ahead All Ordinaries Index. A trading strategy based on a predictive regression underperforms relative to a passive market investment.

We do not envisage that this finding will discourage the search for evidence of return predictability in Australia, since many avenues remain unexplored. The lagged interest rate is just one of many possible variables that might be utilised in a predictive regression. Other variables (such as dividend yield, term spread, momentum) might be explored in place of (or in addition to) the short rate. Of course, in selecting candidate predictors, every effort must be made to consider variables with sound economic rationale. Greater confidence of predictability “evidence” ensues when pre-
dictors have strong theoretical motivation (as opposed to being the outcome of data dredging).

Alternate methodologies might also be explored. The ordinary least squares regression adopted in this paper could be replaced with a more-sophisticated predictive model, such as a probit model that forecasts the probability that the one-month-ahead excess market return is positive. Such an approach allows significantly greater levels of sophistication in implementing trading rules (for example, only switch from equities to fixed income when the probability of an up market is less than x%). Preliminary investigations suggest that, in combination with sophisticated forecasting models, a number of predictors exist in the Australian market that generate superior investment performance.6

A more-thorough analysis should also incorporate the likely effects of transaction costs accumulated by a trading strategy. The trading strategy in this paper underperformed the passive investment so consideration of transaction costs was superfluous. Nonetheless, the trading strategy approach utilised here can easily accommodate transaction costs for entering/Exiting an asset class.

Finally, the analysis can be extended to allow total funds under management to be split between asset classes. The trading strategy in the current paper held either 100 per cent in equities or 100 per cent in fixed income. In combination with a more-sophisticated predictive model, proportional allocations might be adopted according to the strength of the prediction. All of these possibilities are left for future research.

REFERENCES


