ACCOUNTING
& FINANCE

afaanz

Accounting and Finance

Information diffusion and the predictability of New Zealand stock market returns

Hai Lin[a], Daniel Quill[b]

[a]*School of Economics and Finance, Victoria University of Wellington, Wellington, New Zealand*
[b]*Deloitte New Zealand, Wellington, New Zealand*

Abstract

This paper examines the impact of international predictors from liquid markets on the predictability of excess returns in the New Zealand stock market using data from May 1992 to February 2011. We find that US stock market return and VIX contribute significantly to the out-of-sample forecasts at short horizons even after controlling for the effect of local predictors, while the contribution by Australian stock market return is not significant. We further demonstrate that the predictability of New Zealand stock market returns using US market predictors could be explained by the information diffusion between these two countries.

Key words: Information diffusion; International predictors; Liquidity; Out-of-sample; Stock return predictability

JEL classification: G01, G15

doi: 10.1111/acfi.12091

This paper is based on Quill's master thesis titled 'International Factors and Stock Return Predictability: Evidence from the New Zealand Market'. We thank seminar participants at University of Otago, Victoria University of Wellington, Auckland University of Technology, and participants at XMU-UNCC 2012 International Symposium on Risk Management and Derivatives and the 2013 Financial Markets and Corporate Governance Conference for very helpful comments. Lin acknowledges the support from National Natural Science Fund of China (Grant No. 71301137, 71371161, 71101121) and the Humanities and Social Science Fund of Chinese Ministry of Education (Grant No. 11JYC790014).

Received 21 October 2013; accepted 2 July 2014 by Henk Berkman (Editor).

1. Introduction

The question of whether stock returns are predictable has been the focus of an extensive literature on asset prices in the last forty years. A lot of predictors are found to be useful in predicting the stock returns in the US market, such as inflation (Nelson, 1976; Fama and Schwert, 1977; Fama, 1981; Pesaran and Timmermann, 1995), nominal interest rates (Breen *et al*., 1989; Ang and Bekaert, 2007), term spread (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989), default spread (Keim and Stambaugh, 1986; Fama and French, 1989), earnings-to-price ratio (Campbell and Shiller, 1988; Fama and French, 1988), dividend yield (Campbell and Shiller, 1988, 1998; Fama and French, 1988, 1989), book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), pay-out ratio (Lamont, 1998), consumption wealth ratio (Lettau and Ludvigson, 2001) and bond forward rate factor (Cochrane and Piazzesi, 2005).

A large body of literature also questions the existence of stock return predictability. Goetzmann and Jorion (1993) suggest that the R^2 statistics obtained in the tests using dividend yield as a predictor were spuriously high. Similarly, Nelson and Kim (1993) and Stambaugh (1999) show that the variables which are persistent and correlated with the error term result in biased coefficients in finite samples. Stambaugh (1999) finds that the coefficient for the dividend yield is particularly biased, which can lead to over-rejection of the null hypothesis of no predictability. Lo and MacKinlay (1990) argue that repeated revaluations of the same data set can lead to 'data snooping' (data mining) and spurious regressions. Ang and Bekaert (2007) also caution the test statistics of the in-sample regression and point out that they lead to over-rejection of the null of constant expected returns at long horizons.

Compared to the research of return predictability of US stock returns, the predictability of stock returns in other countries is relatively underexplored. Only a few papers have examined this issue and found that the stock returns in other countries are also predicable. In a recent study, Rapach *et al*. (2013) find that the stock returns in a number of non-US industrialised countries could be predicted by the US stock returns. They propose a news diffusion hypothesis to explain such predictability. However, their sample does not include New Zealand. Moreover, they only investigate the news diffusion from the return. Some studies examine New Zealand stock market and look at issues such as return co-movement, contagion, market integration, investor sentiment and US influence, such as Chen and Zhang (1997), Bowman and Iverson (1998), Conover *et al*. (1999), Johnson and Soenen (2002), and Schmeling (2009). These studies focus on the in-sample statistical evidence and do not address the issue of economic significance.

This paper is to examine the information diffusion effect from larger, more liquid stock markets to smaller, less liquid stock markets when the world economy becomes integrated. US and Australian market are regarded as the larger, more liquid markets and then used to test their impacts on the New Zealand stock market, which is smaller and less liquid. In particular, we use the US and Australian stock market return, and VIX as the proxies of international predictors from liquid markets, and test their importance in predicting the excess returns of New Zealand stock market.

There are several characteristics of the New Zealand stock market that differ to the US stock market. As outlined by Jiang *et al.* (2009), the New Zealand stock market has a market capitalisation of 45 per cent of gross domestic product (GDP) compared with the US, which has a market capitalisation of 120 per cent of GDP. Concentration is high in the New Zealand stock market, which is documented by Chin *et al.* (2002, p. 423): ‘the top 10 companies represent 77 per cent of the market, the top 40 represent 95 per cent of the total market and the remaining 170 securities represent around 5 per cent of the market’. Hence, liquidity is an issue when trading in the New Zealand stock market; for example, Pinfold *et al.* (2001) document the difficulties for institutional investors to implement investment strategies based on book-to-market ratio. In a market with many low-capitalisation stocks, it is difficult to buy and sell large volumes of shares of small stocks without incurring price impact. New Zealand is also a small, export-driven economy with significant exposure to the global economy. There are some New Zealand stocks cross-listed in the US, which might also have exposure to the systematic movements in the US markets. If different markets are subject to the same risk because of globalisation, but economic news is reflected first in the more liquid markets and then spills over to the less liquid markets, then information from the larger, more developed and liquid markets should be useful to predict New Zealand stock market returns.

We use two approaches when conducting the empirical studies. We follow out-of-sample analysis to address the return predictability issue. Bossaerts and Hillion (1999), Goyal and Welch (2003), Ang and Bekaert (2007), and Welch and Goyal (2008) found no evidence of out-of-sample forecast. They find that overall, using the historical average forecast to time the market would have been more useful than the predictive regression models. On the other hand, Rapach and Wohar (2006), Campbell and Thompson (2008), and Rapach *et al.* (2010) obtained significant out-of-sample forecast results.

We also conduct the economic significance analysis to test the robustness of stock return predictability, that is, whether a practitioner could profit using the predictive regression models to time the market. Leitch and Tanner (1991) show that profit measures and statistical criteria are only weakly related, which explains why companies often purchase forecasting models even though they underperform the benchmark statistically. It is therefore important to also use profit measures as additional support for predictability even when forecasts have poor statistical performance (Kandel and Stambaugh, 1996). Marquering and Verbeek (2004), Campbell and Thompson (2008) and Rapach *et al.* (2010) all find that the predictive regressions can give economically significant utility gains above the benchmark. They interpret the utility gains as a portfolio management fee that investors would be willing to pay for access to the information. Xu (2004), Campbell and Thompson (2008), and Zhou (2010) found that R^2 statistics that are extremely low in terms of explanatory still infer large performance gains to the portfolio returns.

We find that US stock market return and VIX contribute significantly to the out-of-sample forecasts at short horizons even after controlling for the effect of local factors. We also find that such predictability becomes stronger during the recent financial crisis, which is an evidence of contagion effect.[1] On the other hand, the predictability by Australian stock market return is not significant.

We next show that the predictability of New Zealand stock market returns using US market predictors could be explained by the information diffusion between these two countries. We follow two procedures to test this hypothesis. We first analyse the economic link between New Zealand, US and Australia. We then use Granger causality test, news diffusion model (Rapach *et al.*, 2013) and impulse response analysis (Hong and Stein, 1999) to investigate the speed of contemporaneous information transfer on these markets. The empirical results suggest that the economic link between US and New Zealand is stronger and more relevant in explaining the change of New Zealand GDP. The US markets transfer the contemporaneous information more quickly than New Zealand stock market. There exist information frictions on New Zealand stock market compared with US markets. On the other hand, the economic link between Australia and New Zealand is not so relevant. The speed of information transfer on Australian stock market is not significantly faster than New Zealand stock market either. This explains why the predictors from US market and Australian market perform differently in predicting New Zealand stock market returns.

This paper contributes to the literature of stock return predictability in several ways. Firstly, different from Rapach *et al.* (2013) that test the news diffusion from US stock returns only, our tests use a larger dimension of international predictors to predict New Zealand stock market returns and thus contribute to the understanding of New Zealand stock market from a broader information set perspective. We not only test the news diffusion from the return, but also test the news diffusion from the volatility. Secondly, different from the other studies of New Zealand stock market, we focus on the out-of-sample evidence and conduct both statistical and economic significance analysis. Out-of-sample analysis provides a good way of testing stock return predictability since it avoids the possible statistical issues of the in-sample regressions. The economic significance analysis could have implications for the portfolio management. For example, the utility gains used in this paper as one

[1] Bae *et al.* (2003), Bekaert *et al.* (2005) and Longstaff (2010) define financial contagion as an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market.

economic significance measure could help decide the cost charged to an investor for the access to the information. Thirdly, we also test the performance of a comprehensive number of local predictors in predicting New Zealand stock returns. These tests provide a robust result on whether local variables give useful information for the prediction of New Zealand stock returns. Fourthly, we test the change of predictability from international predictors during the recent financial crisis and provide the further evidence of contagion effect documented in the literature. Finally, we provide a good explanation on why the predictors from US market and Australian market perform so differently in predicting New Zealand stock market.

The remainder of this paper is organised as follows. Section 2 explains the data sources. Section 3 describes the empirical methodology. Section 4 presents the empirical results, and finally Section 5 concludes.

2. Data

This section presents the data used for the predictive regressions. The data sample period is from May 1992 to February 2011. The predictor variable abbreviations which are used for the rest of the paper are expressed in italics inside parentheses.

2.1. Dependent variable

The dependent variable is the aggregate market return in excess of the risk-free rate (*Exrstock*). The aggregate stock market is represented by the New Zealand Stock Exchange All Total Return (dividends included) index and is obtained from Bloomberg. Month-end total index values are used, and log returns are calculated. The 3-month zero-coupon Treasury bond is used as the risk-free rate and is obtained from the Reserve Bank of New Zealand (RBNZ).[2] When calculating excess returns, the risk-free rate is multiplied by (1–0.33) to take into account marginal ordinary taxes faced by investors (Lally and Marsden, 2004).[3]

2.2. Independent variable

The independent variable is a lagged predictor variable. Following Welch and Goyal (2008), a number of macroeconomic and stock characteristic variables are used and several new variables are also introduced. *Treasury Bill (Tbill)* is the 3-month zero-coupon Treasury yield. *Term Spread (TRMS)* is

[2] We thank Leo Krippner to kindly provide the data with us.

[3] There is no capital gain tax in New Zealand. Therefore, we should consider the difference of tax treatment between stock market investment and risk-free investment.

the difference between the long-term yield (10-year zero-coupon Treasury bond yield (*Tbond*)) and the short-term yield (*Tbill*). *Cochrane and Piazzesi (2005) Factor (CP)* factor is a bond forward rate factor using 1- to 5-year zero-coupon bonds. We construct CP factor using the information up to 5 years (CP5) and 10 years (CP10). The data of New Zealand zero-coupon Treasury bonds are obtained from RBNZ. *Inflation (CPI)* data are obtained from RBNZ and are in quarterly frequency. The *Dividend-Price ratio (DivPrice)* is dividends divided by the share price, where dividends are the 1-year moving sum of dividends. The *Dividend Yield (DivYld)* is dividends divided by the lagged share price, where dividends are the 1-year moving sum of dividends. The *Earnings-to-Price ratio (EP)* is earnings divided by the share price, where earnings are the 1-year moving sum of earnings. The *Book-to-Market ratio (BVMV)* is the book value of common equity divided by market value, where the market value is the number of shares outstanding multiplied by the price. The *Pay-out ratio (DivEarn)* is dividends divided by earnings, where dividends and earnings are the 1-year moving sums. The *Return on Equity (ROE)* is the moving sum of earnings over the last year divided by average common equity over the same period. The *Debt-to-Equity ratio (DE)* is debt divided by the book value of common equity. *Stock variance (Svar)* is the sum of the squared daily returns for each month on the New Zealand aggregate stock market.

Financial statement data are collected from Bloomberg, NZX company research and the individual company websites. The data from NZX company research are available in annual frequency, whereas Bloomberg has semi-annual data from as early as 1998. NZX company research contains original financial report data, whereas any re-calculations after financial reports were published are updated on Bloomberg. Therefore, to make sure that the data used are what was ‘available’ at the time, at each date when data are available for both NZX company research and Bloomberg, the NZX company research data are used. Missing data from Bloomberg and NZX company research are also retrieved from the annual reports from individual company websites. The appendix explains on how to calculate the aggregate market variables including the dividend-price ratio, the dividend yield, the earnings-to-price ratio, the book-to-market ratio, the pay-out ratio, the return on equity, the debt-to-equity ratio and stock variance.

The international predictors used in the empirical analysis include US stock market return, Australian stock market return and VIX. The US stock market return is measured by S&P 500 return *(S&P500)*, while the Australian stock market return is measured by the return of the index comprising the 50 largest market capitalisation companies on the Australian stock exchange *(AS31)*. The motivation behind these variables comes from Longstaff *et al*. (2011), who find that US return explains CDS spreads across countries more so than local economic variables. If global economic information is incorporated into the most liquid markets first and then diffuses over to markets where price discovery is slower, then the stock market return in the more developed US and Australian markets should be useful for predicting New Zealand stock market.

The *Chicago Board Options Exchange index of implied volatility (VIX)* measures the 30-day forward-looking implied volatility of the S&P 500 index options. It is commonly viewed as an indicator of market sentiment.[4] International financial markets have become more interrelated, and the effect of this was evident during the US subprime mortgage crisis which spilled over to other markets leading to a global financial crisis (GFC). It is therefore important to test whether changes in this risk indicator can predict stock returns in New Zealand because shocks to the more liquid and analysed US market tend to diffuse more slowly to other markets (Pan and Singleon, 2008).

Table 1 reports the summary statistics of the variables. Panel A reports the summary statistics while Panel B reports the correlations among the predictors. The average monthly return of New Zealand stock market is 0.734 per cent, which is slightly higher than that of US market and Australian market.

3. Empirical methodology

3.1. Predictive regression

When the aggregate stock market excess return (r_{t+1}) is regressed on a lagged predictor variable $x_{i,t}$, the predictor variable is useful for forecasting aggregate stock market excess returns in-sample if the predictor has a statistically significant coefficient:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}. \tag{1}$$

Investors are more interested in the out-of-sample forecasts of the aggregate stock market excess return. The estimated predictor coefficient $\hat{\beta}_i$ over the in-sample period and the value of the predictor variable at the end of the in-sample period are used to make the initial out-of-sample forecast:

$$\hat{r}_{i,IS+1} = \hat{\alpha}_{i,IS} + \hat{\beta}_{i,IS} x_{i,IS}, \tag{2}$$

where *IS* denotes the number of observations used to estimate the parameters to make the out-of-sample forecast for the future period *IS* + 1. As in Welch and Goyal (2008), an expanding information set is used for the out-of-sample forecast, where the parameter estimation period expands as data are used up to the time at which the forecast is made:

[4] Schmeling (2009) evaluates whether consumer confidence, as a proxy for investor sentiment, affects the expected stock returns in 18 countries, including New Zealand. He finds sentiment negatively leads the aggregate stock returns.

Table 1
Summary statistics

Panel A. Summary statistics

	Mean	SD	Min	Max	Observations
Exrstock (%)	0.390	4.285	−15.149	13.421	227
NZXALL (%)	0.734	4.274	−14.808	13.760	227
Tbill (%)	0.513	0.149	0.195	0.833	227
Tbond (%)	0.539	0.074	0.363	0.759	227
TRMS (%)	0.026	0.123	−0.201	0.309	227
CP5 (%)	0.536	1.206	−2.066	4.358	227
CP10 (%)	0.893	2.935	−5.153	10.308	227
CPI (%)	0.577	0.427	−0.800	2.300	227
DivPrice (%)	4.789	1.028	1.275	6.903	227
DivYld (%)	4.636	1.132	0.215	6.532	227
EP (%)	10.327	7.007	0.478	25.197	227
BVMV	0.800	0.455	0.261	1.793	227
DivEarn (%)	0.330	0.324	0.086	1.906	227
ROE (%)	−0.032	16.751	−69.439	39.900	227
DE (%)	0.755	0.116	0.360	1.106	227
Svar	0.684	1.099	0.071	14.098	227
S&P500 (%)	0.524	4.393	−18.564	9.232	227
AS31 (%)	0.463	3.872	−10.961	7.856	227
VIX (%)	20.420	8.152	10.420	59.890	227
Exrstock_L (%)	0.263	4.861	−20.013	14.058	227
Exrstock_S (%)	0.464	4.126	−10.454	13.892	214

Table 1 (continued)

Panel B. Correlation

	Tbill	Tbond	TRMS	CPS	CP10	CPI	DivPrice	DivYld	EP	BVMV	DivEam	ROE	DE	Svar	S&P500	AS31	VIX
Tbill	1.00	0.57	−0.87	0.47	0.35	0.20	−0.23	−0.24	−0.10	−0.33	0.19	0.47	0.22	0.02	−0.01	−0.05	−0.41
Tbond		1.00	−0.08	0.98	0.90	0.02	−0.41	−0.44	−0.47	−0.39	0.46	0.13	−0.10	−0.05	0.06	−0.04	−0.35
TRMS			1.00	0.03	0.13	−0.23	0.03	0.02	−0.17	0.16	0.05	−0.51	−0.32	−0.05	0.05	0.04	0.28
CP5				1.00	0.93	0.00	−0.41	−0.45	−0.49	−0.37	0.47	0.09	−0.16	−0.04	0.07	−0.04	−0.30
CP10					1.00	−0.01	−0.35	−0.42	−0.44	−0.29	0.46	0.04	−0.22	−0.04	0.02	−0.07	−0.22
CPI						1.00	0.15	0.02	0.39	0.20	−0.32	0.17	0.09	−0.04	−0.09	−0.08	−0.06
DivPrice							1.00	0.78	0.10	−0.02	−0.53	−0.19	0.31	0.03	−0.04	−0.04	0.41
DivYld								1.00	0.13	0.01	−0.60	−0.27	0.37	−0.07	0.09	0.06	0.22
EP									1.00	0.87	−0.62	−0.01	0.32	−0.05	−0.23	−0.15	0.29
BVMV										1.00	−0.44	−0.08	0.19	−0.03	−0.21	−0.15	0.36
DivEam											1.00	0.16	−0.41	0.11	0.08	0.00	−0.24
ROE												1.00	−0.32	−0.07	0.07	0.06	−0.40
DE													1.00	0.08	−0.08	0.01	0.15
Svar														1.00	−0.21	−0.32	0.33
S&P500															1.00	0.70	−0.38
AS31																1.00	−0.36
VIX																	1.00

This table reports the summary statistics of the variables used in the empirical analysis. The sample period is from May 1992 to February 2011. Panel A reports the summary statistics of the variables, and Panel B reports the correlation among the predictors.

$$\hat{r}_{i,IS+2} = \hat{\alpha}_{i,IS+1} + \hat{\beta}_{i,IS+1} x_{i,IS+1}. \tag{3}$$

Therefore, the next period ($IS + 1$) uses an additional observation to estimate the parameters to make the next out-of-sample forecast. If the out-of-sample period contains T observations, then the last forecast uses observations $IS + T - 1$ to forecast the excess return at time $IS + T$. A forecast is made at the end of each month for monthly, quarterly and yearly return.

As in Campbell and Thompson (2008) and Welch and Goyal (2008), the benchmark forecast is the historical mean aggregate market excess return. The motivation behind this is that if excess returns are not predictable and follow a random walk with a drift,[5] then the best estimate of the next period excess return is the historical mean. We also follow Campbell and Thompson (2008) to impose investment-theory-motivated restrictions. We set the predictive regression coefficient equal to zero when it has a sign different to that of the coefficient estimated over the full sample, and the forecast equal to zero whenever it is negative, imposing a positive or else zero restriction on the excess return forecast. In our empirical analysis, we compare the out-of-sample performance of the predictive regressions without and with constraints.

3.2. Combination forecast

The 'kitchen sink' model, a multiple regression using the entire set of predictor variables, has performed poorly due to collinearity illustrated by Welch and Goyal (2008). Rapach *et al.* (2010) relate econometric theory with portfolio theory and explain that like the reduced variance of a diversified portfolio of stocks, the predictive forecast variance, and hence accuracy of excess return prediction relative to individual predictors, can be improved by combining the individual forecasts to give a combination forecast.

Following Rapach *et al.* (2010), the combination forecast $\hat{r}_{c,t+1}$ is formed from the weighted sum of the N individual forecasts of $\hat{r}_{i,t+1}$,

$$\hat{r}_{c,t+1} = \sum_{i=1}^{N} \omega_{i,t} \hat{r}_{i,t+1}, \tag{4}$$

where the weight of a mean combination forecast is $\omega_{i,t} = 1/N$ for $i = 1, \ldots, N$. A median and a trimmed mean are also used to construct the weights.[6]

[5] This means the excess stock returns is the equity risk premium plus a random error (Fama, 1970).

[6] Rapach *et al.* (2010) find that these simple combining methods generally perform better than more complicated methods.

3.3. Statistical significance

Following Campbell and Thompson (2008), the benchmark forecast is the historical average excess return,

$$\bar{r}_{IS+t} = \frac{\sum_{j=1}^{IS+t-1} r_j}{IS+t-1}. \tag{5}$$

The statistical significance of the out-of-sample forecasts is examined by comparing the mean squared prediction error (MSPE) of the predictive forecast with that of the historical mean forecast. The following out-of-sample R^2 statistic is calculated as in Campbell and Thompson (2008):

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{t=T} (r_{IS+t} - \hat{r}_{IS+t})^2}{\sum_{t=1}^{t=T} (r_{IS+t} - \bar{r}_{IS+t})^2}, \tag{6}$$

where r is the actual excess return, $\hat{r}$ is the predictive regression forecast and $\bar{r}$ is the historical mean forecast. If the predictive regression is more accurate than the historical mean forecast, then the MSPE for the predictive regression will be smaller, and this outperformance over the historical mean forecast results in a positive R^2_{OS}.

To test whether a R^2_{OS} is statistically greater than zero, we follow Welch and Goyal (2008) and use bootstrap to calculate the critical value. Under the null hypothesis of no predictability, the data generating process is assumed to be

$$r_{t+1} = \alpha + v_{t+1}, \tag{7}$$

$$x_{i,t+1} = \mu_i + \rho_i x_{i,t} + \varepsilon_{i,t+1}. \tag{8}$$

For the individual forecast of the ith predictor, the bootstrap for calculating power assumes the data generating process is

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + v_{i,t+1}, \tag{9}$$

$$x_{i,t+1} = \mu_i + \rho_i x_{i,t} + \varepsilon_{i,t+1}, \tag{10}$$

where both β_i and ρ_i are estimated by OLS using the full sample of observations. We store the residuals for sampling and generate 5000 bootstrapped time series by drawing replacement from the residuals. The initial observation is selected by picking one date from the actual data at random.

For the combination forecast, the bootstrap for calculating power assumes the data generating process is[7]

$$r_{t+1} = \alpha + \frac{1}{N}\sum_{i=1}^{N} \beta_i x_{it} + v_{t+1}, \tag{11}$$

$$x_{i,t+1} = \mu_i + \rho_i x_t + \varepsilon_{i,t+1}, \quad i = 1, \ldots, N. \tag{12}$$

The same bootstrap data are also used to calculate the critical value of forecast encompassing test and economic significance measure that will be discussed later. Since the tests are one-sided, 90, 95 and 99 per cent percentile values of the results from 5000 bootstrap series are used as the critical value of significance at 10, 5 and 1 per cent levels, respectively.

3.4. Forecast encompassing test

Examining the marginal importance of the international variables after accounting for the local variables determines whether the international predictors contain additional useful return prediction information not already contained in the local variables. Using the test statistic developed by Harvey *et al.* (1998), the information contained in the combination forecast which excludes S&P500 and VIX is compared with the forecast which includes these variables. Essentially, the MHLN statistic tests whether the combination forecast i encompasses the combination forecast j. First, by defining

$$d_{IS+t} = \left(\hat{u}_{i,IS+t} - \hat{u}_{j,IS+t}\right)\hat{u}_{i,IS+t}, \tag{13}$$

where $\hat{u}_{i,IS+t} = r_{IS+t} - \hat{r}_{i,IS+t}, \hat{u}_{j,IS+t} = r_{IS+t} - \hat{r}_{j,IS+t}$. The modified HLN test statistic is

$$MHLN = \left[\frac{(T-1)}{T}\right]\left[\hat{V}\left(\bar{d}\right)^{1/2}\right]\bar{d}, \tag{14}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_{IS+t}$, $\hat{V}\left(\bar{d}\right) = \frac{1}{T}\hat{\phi}_0$, and $\hat{\phi}_0 = \frac{1}{T}\sum_{t=1}^{T}\left(d_{IS+t} - \bar{d}\right)^2$. Hodrick (1992) adjusted standard errors are used to correct for overlapping

[7] Rapach *et al.* (2010) shows that the mean combination forecast is a forecast from a restricted multiple regression with each of the multiple regression slope coefficients being $1/N$ of individual regression slope coefficients.

residuals at quarterly and yearly forecast horizons. We then use bootstrap method to calculate the p-value of MHLN test statistics.

3.5. Economic significance

The expected return to a portfolio that combines the aggregate stock market and the risk-free asset is

$$E\left[r_p\right] = w(E(r_A)) + (1 - w)r_f, \tag{15}$$

where r_p is the portfolio return, w is the weight in the aggregate stock market, r_A and r_f are the return to the risky asset and risk-free asset, respectively. The choice of asset allocation between the risk-free asset and the aggregate stock market determines the performance of the portfolio. The economic significance of the out-of-sample forecasts is examined, as in Campbell and Thompson (2008), by the change in utility for an investor with mean variance preferences who uses either the historical average or the predictive regression forecast to construct an optimal portfolio. Realistic portfolio constraints are imposed when each forecast is made confining the weight in the aggregate stock market to range between 0 and 150 per cent. The investor seeks to maximise the following objective function:

$$U = E\left[r_p\right] - 0.5\gamma\sigma_p^2. \tag{16}$$

The optimal portfolio weight in the aggregate stock market when the excess return forecast is estimated using the historical mean is

$$w_{IS+t} = \frac{\bar{r}_{IS+t+1}}{\gamma\sigma^2_{IS+t+1}}, \tag{17}$$

where the weight in the aggregate stock market is determined at time $IS + t$ for an investment in the next period $IS + t + 1$. The weight also depends on the variance forecast of the aggregate stock market next period and the investor's risk aversion. As in Campbell and Thompson (2008), a rolling 5-year window of monthly data is used to estimate the aggregate stock market variance and the risk aversion coefficient γ is set to three. When the predictive regression is used, the optimal weight in the aggregate stock market is

$$w_{IS+t} = \frac{\hat{r}_{IS+t+1}}{\gamma\sigma^2_{IS+t+1}}. \tag{18}$$

If the average out-of-sample utility gains are greater using the predictive regression forecast compared with the historical mean forecast, then the predictive regression approach is economically significant.

To do a robustness check, we also use two other economic significance measures, including the changes in the annualised Sharpe ratio from using the forecast of the predictive regression relative to the historical mean and the risk-adjusted abnormal return of the predictive model relative to historical mean suggested by Goetzmann *et al.* (2007, hereafter GISW). We calculate the change of Sharpe ratio and GISW measures as the robustness check of realised utility gains to gauge the economic significance of return predictability.

4. Empirical results

4.1. Out-of-sample forecast

It is important to have an in-sample period that is long enough to give reliable parameter estimates, and at the same time, the out-of-sample period needs to be as long as possible to give the highest forecast power (Hansen and Timmermann, 2011). Our out-of-sample forecast starts in 2002 so that we could have at least 10 years data to estimate the parameters and have another 10 years data to run the out-of-sample test.[8]

Table 2 reports the R^2_{OS} statistics for the monthly, quarterly and yearly return. We report both the unconstrained and constrained results. There are not many individual local predictors that give significant R^2_{OS} results. The local predictors including TRMS (quarterly), EP (monthly and quarterly), ROE (monthly), DE (monthly, quarterly and yearly) and Svar (monthly) show some predicting powers out-of-sample.[9] We also find significant R^2_{OS} statistics for S&P 500 and VIX on monthly returns. These results show the importance of predictors in US markets on predicting New Zealand stock market returns out-of-sample. The R^2_{OS} statistics of S&P 500 is the highest among all the predictors of monthly return using the unconstrained forecast (13.80 per cent) or using the constrained forecast (9.31 per cent). On the other hand, the R^2_{OS} of AS31 is not significant. The CP factors (CP5 and CP10) are not useful for the out-of-sample predictions of New Zealand stock market. This is different from the findings of Cochrane and Piazzesi (2005) that the CP factor is useful in US market. The results of constrained forecast are quite similar to those of unconstrained forecast.

[8] We also run the whole in-sample regressions, and the results are not reported for brevity. We also tried the out-of-sample forecast from 1997 and obtained similar results. They are available upon request.

[9] We also found the inconsistency between in-sample and out-of-sample performance, which is consistent with the findings of Welch and Goyal (2008) and Rapach *et al.* (2010).

Table 2
Out-of-sample forecast: statistical significance

	R^2_{OS}					
	Monthly		Quarterly		Yearly	
	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained
Tbill	−0.36	−0.36	2.35	2.35	4.42	−0.51
Tbond	0.17	0.17	0.13	0.13	−3.87	−3.64
TRMS	0.55	0.57	4.03[c]	3.68[c]	10.19	9.99
CP5	−0.44	−0.48	−0.05	−0.27	−2.84	−2.39
CP10	−0.29	−0.28	0.43	0.16	−2.29	−1.67
CPI	1.86[b]	1.54[c]	2.92[c]	2.27	2.39	3.85
DivPrice	0.42	0.91	−1.78	−0.67	−9.47	−7.52
DivYld	−3.40	−2.94	−6.00	−5.71	−12.24	−11.00
EP	1.91[b]	1.40[c]	6.05[b]	4.49[c]	11.74	8.73
BVMV	−0.03	−0.01	−0.33	−0.33	−0.69	−0.69
DivEarn	0.59	0.59	2.22	2.22	4.15	4.59
ROE	0.77[c]	0.78	2.30	2.26	4.19	4.19
DE	1.45[b]	1.45[b]	6.19[b]	6.19[b]	22.71[b]	21.05[b]
Svar	4.90[c]	2.99[b]	1.85	1.83	0.63	0.63
AS31	3.07	3.68	4.21	4.24	−2.22	−2.22
S&P500	13.80[b]	9.31[b]	1.22	2.64	−1.88	−1.88
VIX	5.27[b]	3.23[b]	0.88	0.21	−3.56	−2.21
Combination forecast						
CM1	2.66[a]	1.97[a]	3.25[b]	2.92[c]	3.91	3.46
CM2	1.53[a]	1.59[a]	1.22[c]	1.40[c]	1.60	1.21
CM3	2.52[a]	2.01[a]	2.87[b]	2.73[c]	3.18	2.91

This table reports R^2_{OS} statistics for the monthly, quarterly and yearly return. The dependent variable is the aggregate market excess return which is the log return of NZX ALL index Total returns (dividends included) in excess of the 3-month Treasury bill rate. The independent variable is a lagged predictor variable. The out-of-sample forecast starts in 2002. Both unconstrained and constrained results are reported. Three combination approaches, that is, simple mean (CM1), median (CM2) and trimmed mean (CM3), are used to calculate the combination forecast. The statistical significance of the R^2_{OS} is based on the p-value of 5000 bootstrap series corresponding to the one-sided test: $H_0 : R^2_{OS} = 0$ against $H_A : R^2_{OS} > 0$.
[a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

Consistent with Rapach *et al*. (2010), the combination forecast gives a much more stable and highly significant R^2_{OS} regardless of whether economic restrictions are imposed. At the monthly forecast horizon, all three combination methods give positive R^2_{OS} which are statistically significant. At all forecast horizons, the combination forecasts give R^2_{OS} which are smaller than the best individual predictors; however, the combination forecasts present a safer forecast for an investor which is uncertain about the best forecasting model and parameter stability (Rapach *et al*., 2010).

4.2. Out-of-sample forecast and the business cycle

Fama and French (1989) find that when economic growth is low, expected returns are high, and when economic growth is high, expected returns are low. They indicate that this is the result of time-varying risk aversion. Investors require a higher compensation to put money in risky stocks when the market is down and therefore expected returns are higher.

Figure 1 depicts the excess return forecasts using the individual predictive regressions and the combination method. The quarterly forecast horizon is used because GDP growth data are quarterly. The vertical lines indicate the peak and troughs of the recent business cycles. There is an upward spike in the return forecasts as GDP reaches the trough in the recession.

Relative to the historical mean forecast, the individual forecasts are still very noisy, even when restrictions are imposed. The combination forecast is very smooth compared with the individual forecasts, consistent with the findings of Rapach *et al*. (2010) that combining the forecast reduces the volatility. On the other hand, the historical mean forecast is too unresponsive, especially during the recent financial crisis period. The historical mean forecast disregards information contained in business cycle fluctuations.

4.3. Forecast encompassing test

Table 3 reports the MHLN statistics for the out-of-sample forecasts. MHLN statistics are also calculated for the forecast which removes S&P500 or VIX separately from the combination forecast. Panel A reports the results of unconstrained forecast while Panel B reports the results of constrained forecast.

At the monthly forecast horizon, including S&P500 return and VIX in the combination forecast is very important for return prediction, as indicated by the highly significant MHLN statistics. This result is quite robust with or without constraints. With or without constraints, the MHLN statistics reject the null at the 1 per cent level. Between the two international predictors, S&P500 has more significant results, which suggests it is a more important international predictor. VIX also show some contributions for the out-of-sample combination forecast. On the other hand, the CP factors including CP5 and CP10 do not contribute the forecast at all. All of the statistics are negative and insignificant.

When the forecasts are extended to longer quarterly and yearly horizons, international predictors no longer contribute to the combination forecast, as indicated by the insignificant MHLN. This suggests that US market predictors provide useful information in addition to the other predictors at short horizons, whereas at longer horizons the information from US market predictors is contained in the local factors.

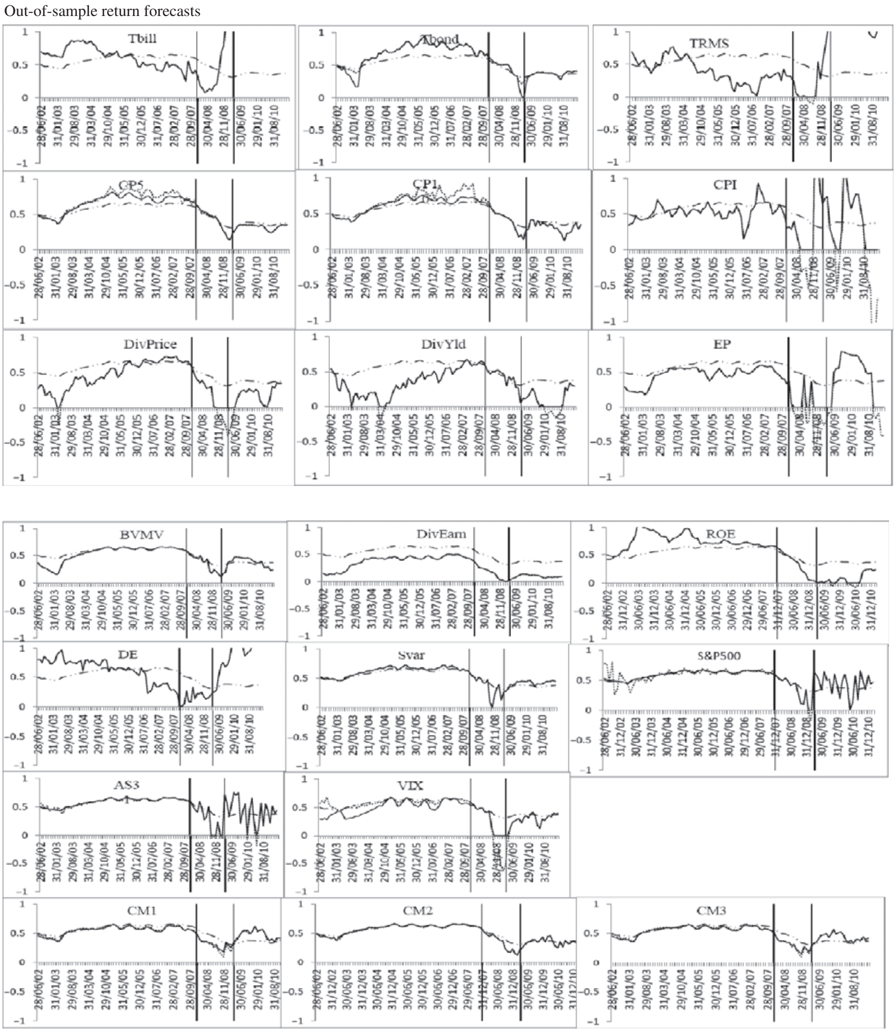

Figure 1 Out-of-sample return forecasts. This figure displays the out-of-sample quarterly excess return forecasts for the individual predictors and the combination forecast from 2002 to 2011. The solid (dotted) line corresponds to the forecast with (without) Campbell and Thompson (2008) constraints, and the dash line corresponds to the historical average forecast.

4.4. Economic significance

Table 4 reports the results of economic significance of out-of-sample forecasts. The portfolio is rebalanced monthly when constructing the optimal portfolios. Three annualised measures are reported for both the unconstrained

Table 3
Forecast encompassing test results

	MHLN test statistics			
	S&P500	VIX	S&P500 and VIX	CP factors
Panel A. Unconstrained forecast				
Mean combination forecast				
Monthly	4.15[a]	1.41[c]	3.22[a]	−2.81
Quarterly	−0.20	−0.19	−0.21	−0.94
Yearly	−0.22	−0.23	−0.26	−0.79
Median combination forecast				
Monthly	4.09[a]	2.10[b]	3.41[a]	−0.92
Quarterly	−0.32	−0.38	−0.48	−0.41
Yearly	0.13	−0.72	−0.29	−0.60
Trimmed mean combination forecast				
Monthly	3.92[a]	1.49[b]	3.24[a]	−2.96
Quarterly	−0.17	−0.21	−0.17	−0.91
Yearly	−0.18	−0.22	−0.21	−0.74
Panel B. Constrained forecast				
Mean combination forecast				
Monthly	4.96[a]	1.40[c]	4.82[a]	−2.60
Quarterly	0.00	−0.67	−0.40	−1.17
Yearly	−0.37	−0.44	−0.55	−0.79
Median combination forecast				
Monthly	3.70[a]	1.84[b]	3.14[a]	−1.24
Quarterly	0.06	−0.20	−0.25	−0.33
Yearly	0.11	−0.58	−0.15	−0.48
Trimmed mean combination forecast				
Monthly	4.69[a]	1.35[c]	5.02[a]	−2.96
Quarterly	0.04	−0.73	−0.37	−1.23
Yearly	−0.28	−0.43	−0.49	−0.77

The table reports the values of the Harvey *et al.* (1998) MHLN statistic for the combination forecast at monthly, quarterly and yearly forecast horizons. The out-of-sample forecast starts in 2002. Panel A presents the unconstrained forecasts and Panel B presents the constrained forecasts. The MHLN statistic is used to test the contribution of international predictors and CP factors after controlling the other predictors. Hodrick (1992) adjusted standard errors are used to correct for overlapping residuals at the quarterly and yearly forecast horizon. The statistical significance of MHLN statistics is based on the p-value of 5000 bootstrap series. [a], [b] and [c] indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4
Out-of-sample forecast: economic significance

	Utility gains				Change of Sharpe ratio				GISW			
	Monthly		Quarterly		Monthly		Quarterly		Monthly		Quarterly	
	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained
Tbill	4.05[c]	4.05[c]	3.75[c]	3.75[c]	0.26[c]	0.26	0.25[c]	0.25[c]	4.14[b]	4.14[c]	3.78[c]	3.78[c]
Tbond	0.17	0.17	0.13	0.36	0.00	0.00	0.01	0.03	0.19	0.19	0.09	0.32
TRMS	4.12[b]	4.12[b]	5.38[b]	5.38[b]	0.24[c]	0.24[c]	0.37[b]	0.37[b]	4.22[b]	4.22[b]	5.41[b]	5.41[b]
CP5	−0.30	−0.21	0.58	0.52	−0.02	−0.02	0.04	0.03	−0.30	−0.21	0.57	0.51
CP10	−0.19	−0.19	0.47	0.47	−0.04	−0.04	0.03	0.02	−0.15	−0.15	0.47	0.47
CPI	4.78[b]	4.78[b]	3.32[b]	3.32[c]	0.30[c]	0.30[c]	0.21[c]	0.21[c]	4.93[b]	4.93[b]	3.40[b]	3.40[c]
DivPrice	1.87	1.87	2.16	2.16	0.06	0.06	0.12	0.12	2.01	2.01	2.23	2.23
DivYld	−5.57	−5.57	−4.25	−4.25	−0.50	−0.50	−0.37	−0.37	−5.58	−5.58	−4.28	−4.28
EP	2.76[c]	2.76[c]	4.12[b]	4.12[b]	0.15	0.15	0.27[c]	0.27[c]	2.82[c]	2.82[c]	4.18[b]	4.18[b]
BVMV	−0.03	−0.03	0.09	0.09	−0.01	−0.01	0.00	0.00	−0.02	−0.02	0.07	0.07
DivEarn	1.22	1.22	2.75[c]	2.75[b]	0.04	0.04	0.16	0.16[c]	1.35	1.35	2.89[c]	2.89[b]
ROE	1.33	1.33	1.74	1.74	0.07	0.07	0.11	0.11	1.41	1.41	1.78	1.78
DE	4.68[b]	4.68[b]	5.65[b]	5.65[b]	0.29[c]	0.29[c]	0.38[b]	0.38[b]	4.84[b]	4.84[b]	5.76[b]	5.76[b]
Svar	5.86[c]	5.86[c]	3.03	3.03	0.37[c]	0.37[c]	0.19	0.19	5.96[c]	5.96[c]	3.06	3.06
AS31	6.23	6.96	6.53	6.72	0.39	0.45	0.44	0.45	6.36	7.09	6.57	6.76
S&P500	13.05[b]	13.05[b]	3.72	4.42	0.94[c]	0.94[c]	0.24	0.29	13.21[b]	13.21[b]	3.73	4.43
VIX	4.97[b]	4.97[b]	2.42	1.86	0.31[b]	0.31[b]	0.15	0.10	5.10[b]	5.10[b]	2.45[c]	1.89
Combination forecast												
CM1	4.99[a]	3.45[b]	3.37[b]	2.89[b]	0.31[b]	0.21[b]	0.21[c]	0.18[b]	5.12[a]	3.57[b]	3.45[b]	2.96[c]
CM2	2.85[a]	2.86[a]	2.02[b]	2.03[b]	0.16[a]	0.16[a]	0.12[b]	0.12[b]	2.96[a]	2.97[a]	2.05[b]	2.06[b]
CM3	4.58[a]	3.44[b]	2.96[b]	2.73[b]	0.28[a]	0.20[b]	0.19[c]	0.17[b]	4.70[a]	3.56[b]	3.03[b]	2.79[c]

This table reports the economic significance of out-of-sample forecast. The out-of-sample portfolio choice starts in 2002. Three different measures of economic significance are reported: utility gains, change of Sharpe ratio and Goetzmann *et al*. (2007, GISW). To determine the weight in the stock, it is assumed the investor estimates the variance using a 5-year rolling window of monthly data following Campbell and Thompson (2008). The realistic portfolio constraints are imposed when each rebalance is made confining the weight in the stock market to range between 0% and 150%. The measures relative to the benchmark forecast are reported for both the unconstrained forecasts (Unconstrained) and the constrained forecasts (Constrained). The significance is based on the *p*-value of 5000 bootstrap series.
[a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

forecast and constrained forecast, including the utility gains, the change of Sharpe ratio and the GISW.[10]

At the monthly forecast horizon, S&P500 gives the highest average annualised utility gain of 13.05 per cent, and VIX gives 4.97 per cent by unconstrained forecast. Constrained forecast give similar results. Both of them are significant at 5 per cent level. These utility gains are higher than most of the local predictors and very economically significant. However, the utility gain by AS31 is not significant. The utility gains of S&P500 return and VIX become much lower at the quarterly horizon. The change of Sharpe ratio and the GISW show similar results. This again shows the importance of international predictors in predicting the short term return of New Zealand stock market. Similarly, CP factor fails to give a significant utility gain. Combination forecast gives stable and significant results.

4.5. Out-of-sample forecast and the GFC

Rapach *et al.* (2010) find that the out-of-sample predictability performance is heightened during periods of low economic growth. Similarly, Henkel *et al.* (2011) find that predictability is non-existent during economic expansions and that the performance of predictors relies on the proportion of recession months available in the data sample. Determining in which state of the economy predictability is most evident allows an investor to determine when predictive regression forecasts are most useful for timing the market. Our sample covers the recent financial crisis period and therefore provides a good example to test the performance of out-of-sample forecast under different economic states.

We follow Dick-Nielsen *et al.* (2012) and define the period from quarter two, 2007 to quarter two, 2009 to be the GFC period. Table 5 reports the out-of-sample forecast during the GFC and non-global financial crisis (Non-GFC) period. Both R^2_{OS} and utility gain results are reported.[11] Panel A reports the monthly results while Panel B reports the quarterly results.

All of the combination forecasts and the majority of the individual variables display heightened out-of-sample stock return predictability during the recent financial crisis period. The utility gains are also strikingly higher than those generated in the non-financial crisis period. The importance of S&P500 and VIX also becomes much higher during the financial crisis period. For the monthly unconstrained forecast, the R^2_{OS} of S&P500 is 17.25 per cent during

[10] These measures do not take into account transaction costs; however, Campbell and Thompson (2008) argue that transaction costs from market timing strategies are less of a concern because the historical mean strategy incurs them as well. They indicate that because the benchmark forecast strategy also involves transaction costs, utility gains of 0.5 per cent are enough to compensate for additional costs.

[11] The results of the change of Sharpe ratio and the GISW are similar to those of utility gains and not reported for brevity. They are available upon request.

Table 5
Out-of-sample forecast and the global financial crisis

	Panel A. Monthly forecast								Panel B. Quarterly forecast							
	Unconstrained forecast				Constrained forecast				Unconstrained forecast				Constrained forecast			
	R^2_{OS}		Utility gains		R^2_{OS}		Utility gains		R^2_{OS}		Utility gains		R^2_{OS}		Utility gains	
	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC	GFC	Non-GFC
Tbill	0.23	−0.96	10.26	1.75	0.23	−0.96	10.26	1.75[a]	8.49	−7.19	8.59	1.95	8.49	−7.19	8.59	1.95
Tbond	0.50	−0.16	1.14	−0.19	0.50	−0.16	1.14	−0.19	−1.69	2.15	−1.10	0.59	−2.11	1.77	−0.46	0.67
TRMS	5.13	−4.13	20.91[c]	−2.07	5.06[b]	−4.04	20.91[b]	−2.07	17.98	−17.64	20.05[c]	−0.03	17.40[b]	−17.64	20.05[b]	−0.03
CP5	−0.49	−0.38	−0.46	−0.24	−0.66	−0.29	−0.10	−0.26	−0.92	1.29	1.08	0.40	−1.09	1.00	1.01	0.34
CP10	1.12	−1.72	3.75	−1.67	1.00	−1.59	3.75	−1.67	0.04	1.04	2.08	−0.13	0.32	−0.08	2.13	−0.16
CPI	8.64[c]	−5.09	23.47[b]	−2.10	4.66	−1.66	23.47[c]	−2.10	12.15	−11.42	17.29[c]	−1.83	7.04	−5.14	17.29[c]	−1.83
DivPrice	3.07	−2.29	15.22	−3.05	3.83	−2.08	15.22	−3.05	2.58	−8.55	13.04	−1.85	3.90	−7.76	13.04	−1.85
DivYld	−0.57	−6.29	−1.28	−7.20	−0.53	−5.40	−1.28	−7.20	−1.43	−13.09	−1.83	−5.18	−1.43	−12.35	−1.83	−5.18
EP	5.26	−1.52	12.92	−0.98	3.83	−1.09	12.92	−0.98	13.26	−5.17	15.23[c]	0.04	10.20	−4.38	15.23	0.04
BVMV	0.26	−0.32	1.16	−0.46	0.26	−0.28	1.16	−0.46	0.56	−1.70	1.01	−0.25	0.56	−1.70	1.01	−0.25
DivEarn	2.43	−1.29	8.50	−1.46	2.43	−1.29	8.50[c]	−1.46	7.82	−6.49	15.60[b]	−1.96	7.82[c]	−6.49	15.60[b]	−1.96
ROE	0.99	0.55	4.76	0.08	0.99	0.56	4.76	0.08	−0.26	6.28[b]	4.33	0.80	−0.26	6.18[b]	4.33	0.80
DE	4.05	−1.21	15.05[c]	0.90	4.05	−1.21	15.05[c]	0.90	12.15[c]	−3.06	18.60[b]	0.93	12.15	−3.06	18.60[c]	0.93
Svar	8.17	1.55	18.18[c]	1.31	4.40	1.55	18.18[c]	1.31	2.33	1.09	10.10	0.41	2.30	1.09	10.10	0.41
AS31	4.10	2.02	16.60	2.39	4.25	3.11	16.60	3.40	5.65	1.96	17.51	2.48	5.41	2.42	17.51	2.74
S&P500	17.25[c]	10.26[c]	35.12[b]	4.99	10.39[c]	8.21	35.12[c]	4.99	2.89	−1.37	10.17	1.31	3.03	2.03	10.17	2.28
VIX	8.29[c]	2.18[c]	16.66[c]	0.66	4.74	1.69	16.66[c]	0.66	2.40	−1.48	8.88	0.03	2.74	−3.73	8.88	−0.74
Combination forecast																
CM1	4.64[a]	0.65	16.16[a]	0.87	3.27[b]	0.65	10.50[a]	0.85	5.75[c]	−0.63	10.80[a]	0.64	5.15[c]	−0.57	8.66[b]	0.77
CM2	2.58[a]	0.46	9.40[a]	0.43	2.56[a]	0.59	9.40[a]	0.45	2.21[c]	−0.22	6.30[a]	0.43	2.27[c]	0.18	6.34[a]	0.44
CM3	4.34[a]	0.66	14.80[a]	0.81	3.34[b]	0.65	10.78[a]	0.74	4.96[c]	−0.36	9.44[a]	0.58	4.72[c]	−0.41	8.47[a]	0.61

This table reports the out-of-sample forecast during the global finance crisis (GFC) and non-global financial crisis period (Non-GFC). The out-of-sample forecast starts in 2002. The global financial crisis is from Q2 2007 to Q2 2009. Panel A reports the results of monthly return forecast while Panel B reports the results of quarterly return forecast. Both R^2_{OS} and the utility gains are reported for both the unconstrained forecast and the constrained forecast. The significance is based on the *p*-value of 5000 bootstrap series.

[a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

the financial crisis period but is only 10.26 per cent during the non-financial crisis period. The utility gain of S&P500 is 35.12 per cent and much higher than that of non-financial crisis period (4.99 per cent). VIX gives similar results. The stronger out-of-sample performance of S&P500 and VIX in determining future short-horizon returns in New Zealand during the recent financial crisis demonstrates the importance of contagion effect.

4.6. Out-of-sample prediction and size

Kong *et al.* (2011) find that individual economic variables are generally unable to outperform the historical mean forecast across size base portfolios. The combination forecast is useful, but the difference in predictability of small compared with large capitalisation stocks is minimal. However, they do find that small capitalisation stocks are more predictable than large capitalisation stocks when lagged industry returns are used, arguing that information frictions are higher for smaller companies. It is therefore likely that economic information (particularly from the international predictors) will transmit more slowly to smaller and more illiquid stocks in the New Zealand stock market, resulting in more predictable future excess returns.

The NZX Small Cap and NZX10 total return indexes are retrieved from Bloomberg. The 10 largest stocks in the New Zealand market comprise the NZX10, whereas the Small Cap index contains the companies in the NZX ALL which are too small to be included in the top 50 index (NZX50).[12] Therefore, comparing the largest and smallest companies is useful for determining whether there are any differences in the most liquid and frequently traded stocks compared with the more illiquid and thinly traded stocks.

Table 6 reports the out-of-sample forecast for large stock index excess returns (large) and small stock index excess returns (small). Both R^2_{OS} and utility gain results are reported.[13] Panel A reports the monthly results while Panel B reports the quarterly results.

Similar to the findings for the aggregate market, the combination forecast is very consistent across large and small capitalisation stocks and gives statistically significant R^2_{OS} for both indexes at monthly horizon. The results also indicate that S&P500 has significant predictive power for large and small capitalisation stocks. The predictive power is a lot higher for the small stocks compared with the large stocks. The ability to outperform the historical average forecast is considerably higher for the Small Cap index compared with the NZX10 when S&P500 is used as a predictor. For the monthly unconstrained forecast, S&P500 gives an R^2_{OS} of 9.53 per cent for the

[12] The last two rows of Panel A of Table 1 report the summary statistics of NZX10 ($Exrstock_L$) and NZX Small Cap index ($Exrstock_S$).

[13] The results of the change of Sharpe ratio and the GISW are similar to those of utility gains and are not reported for brevity. They are available upon request.

Table 6
Out-of-sample forecast and the size

	Panel A. Monthly return forecast								Panel B. Quarterly return forecast							
	Unconstrained forecast				Constrained forecast				Unconstrained forecast				Constrained forecast			
	R^2_{OS}		Utility gains		R^2_{OS}		Utility gains		R^2_{OS}		Utility gains		R^2_{OS}		Utility gains	
	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small
Tbill	0.41	−3.34	4.68[b]	3.55[b]	0.41	−3.43	4.68[b]	3.55[c]	4.09[c]	−0.07	4.47[b]	2.40	3.96[c]	−0.07	4.47[b]	2.40
Tbond	0.15	−0.27	0.38	−0.25	0.15	−0.27	0.38	−0.25	−0.38	−4.01	0.44	−1.70	−1.15	−4.01	0.58	−1.70
TRMS	0.69[c]	0.00	4.57[b]	1.87	0.58	0.04	4.57[b]	1.87	4.98[b]	2.77	3.93[b]	2.84[c]	3.21[c]	2.77	3.93[b]	2.84[c]
CP5	−0.61	−3.75	−0.74	−1.94	−0.46	−3.75	−0.67	−1.94	−0.35	−3.93	0.68	−2.42	−0.43	−3.93	0.36	−2.42
CP10	−1.01	−2.18	−1.03	−2.24	−0.81	−2.18	−1.00	−2.24	0.02	−2.11	0.78	−2.23	−0.08	−2.11	0.26	−2.23
CPI	2.29[b]	−3.43	4.57[b]	2.73[c]	1.74[c]	−2.25	4.57[b]	2.73[c]	3.04[c]	−0.42	3.38[c]	2.45[c]	2.10	−0.39	3.38[c]	2.45[c]
DivPrice	−0.04	−1.24	1.67	1.21	0.35	1.00	1.67	1.95	−2.24	−2.65	1.32	0.70	−1.08	−1.85	1.32	−1.22
DivYld	−3.74	0.54	−2.86	1.69	−1.88	0.54	−2.86	1.69	−6.91	1.03	−2.99	1.08	−4.93	1.02[c]	−2.99	1.07
EP	0.98[c]	1.10[c]	2.41[c]	3.32[b]	0.75	1.33	2.41	3.36[c]	4.24[c]	2.81	2.78[c]	4.20[b]	2.31	2.06	2.78[c]	3.94[b]
BVMV	−0.09	−0.81	−0.08	−0.32	−0.08	−0.81	−0.08	−0.32	−1.01	−0.41	0.06	−0.24	−0.86	−0.41	0.06	−0.24
DivEarn	0.02	0.05	0.37	0.72	0.00	0.02	0.33	0.72	1.02	1.56	1.94	2.69[c]	1.08	1.56	1.94[c]	2.69[c]
ROE	0.55	−3.22	1.65	−4.17	0.91	−2.25	1.65	−4.17	1.89	−4.45	1.70	−2.89	2.47	−3.26	1.70	−2.89
DE	1.57[b]	−0.45	5.36[b]	−0.57	1.50[c]	−2.17	5.36[b]	−4.63	7.48[b]	0.56	4.97[b]	0.65	6.41[b]	−0.54	4.97[b]	−0.27
Svar	3.66	6.75[b]	4.31[c]	6.69[b]	1.97[c]	3.40[b]	4.31[c]	6.69[b]	1.26	3.52[c]	1.85	4.94[b]	1.15	2.78[c]	1.85	4.94[b]
AS31	−1.93	21.99[a]	−2.44	18.21[a]	1.30	14.15[b]	2.32	18.21[a]	1.95	12.01[b]	2.69	11.95[b]	2.20	9.58[b]	3.60	11.95[b]
S&P500	9.53[c]	25.11[a]	11.78[c]	14.98[a]	5.95[c]	14.28[a]	11.78[c]	14.98[a]	0.72	5.73[c]	2.01	8.27[c]	1.75	5.84[c]	2.81	8.70[c]
VIX	4.26[b]	0.72	5.43[c]	2.77	2.49[c]	−0.66	5.43[c]	−1.06	1.42	−11.44	1.97	−2.17	0.54	−0.02	1.90	0.15
Combination forecast																
CM1	1.74[a]	3.95[a]	3.88[a]	6.63[a]	1.35[b]	2.33[b]	3.31[b]	2.69[b]	3.00[b]	2.37	3.21	1.95	2.44	2.94[c]	2.57[b]	1.25
CM2	0.87[a]	0.49[b]	1.85[a]	0.83[b]	0.91[b]	0.82[c]	1.92[a]	0.96[b]	1.16[c]	0.62	1.71[b]	0.49	1.26[c]	1.59	1.87[b]	0.93[c]
CM3	1.60[a]	3.51[a]	3.67[a]	5.71[a]	1.28[b]	2.42[b]	3.14[a]	3.00[b]	2.48[b]	2.21[c]	2.82[b]	2.07[c]	2.12[c]	2.93[c]	2.42[b]	1.50[c]

This table reports the out-of-sample forecast of large capitalisation stocks (large) and small capitalisation stocks (small). The large capitalisation stocks are represented by the NZX10 index while the small capitalisation stocks are represented by the NZX Small Cap index. The out-of-sample forecast starts in 2002. Panel A reports the results of monthly return forecast while Panel B reports the results of quarterly return forecast. Both R^2_{OS} and the utility gains are reported for both the unconstrained forecast and the constrained forecast. The significance is based on the p-value of 5000 bootstrap series.

[a], [b] and [c] indicate significance at the 1%, 5% and 10% levels, respectively.

NZX10 and a much higher R^2_{OS} of 25.11 per cent for the Small Cap index. Constrained forecast gives similar results. An explanation for this is that smaller, less traded stocks are less closely watched and therefore exhibit greater predictability.[14] The international information takes longer to affect the prices of small capitalisation stocks compared with the prices of larger capitalisation stocks in New Zealand, which reflect new information more quickly.

Further support for this is provided by the strikingly high increase of AS31 return to predict Small Cap stocks compared with the aggregate market and NZX10. AS31 underperforms the historical average for the NZX10, whereas it greatly outperforms the historical average when the Small Cap index is considered. For the monthly unconstrained forecast, the R^2_{OS} for AS31 is 21.99 per cent for the Small Cap index, which is strikingly higher than the R^2_{OS} of -1.93 per cent for the NZX10. This suggests that the information which is reflected in the AS31 is also quickly reflected in the prices of companies in the NZX10, whereas this information takes considerably longer to be reflected in the Small Cap index.

The annualised utility gains for optimal portfolio construction using S&P500 and AS31 confirm the findings of R^2_{OS}. The utility gains are higher (lower) for the Small Cap (NZX10) index compared with the aggregate market, with S&P500 and AS31 giving utility gains of 14.98 per cent (11.78 per cent) and 18.21 per cent (-2.44 per cent), respectively, for the monthly unstrained forecast. Monthly constrained forecast gives similar conclusions. The significance becomes much weaker for quarterly return forecast but similar results still hold.

On the other hand, at the monthly forecast horizon, VIX significantly outperforms the historical average in predicting the NZX10 index returns, whereas the predicting power is much lower for the Small Cap index returns. If unconstrained forecast is used for monthly return, the R^2_{OS} of the NZX10 is 4.26 per cent and significant at 5 per cent level, whereas it is only 0.72 per cent and insignificant for the Small Cap index. Similarly, the utility gain of the NZX10 is 5.43 per cent, whereas it is only 2.77 per cent for the Small Cap index. This is consistent with the findings of Bansal *et al*. (2011), who find that liquid stocks are more responsive to VIX shocks. They suggest that because price impact is higher for small illiquid stocks, when sentiment changes investors sell more liquid stocks when adjusting their portfolios towards treasury securities. This indicates that VIX has more of an impact on the NZX10 index, and therefore, its future returns compared with the Small Cap index due to trading on risk appetite. The larger capitalisation stocks are also likely to be more globalised compared with smaller and local companies, and therefore, market sentiment in the international market has more of an impact on these companies.

[14] Brennan *et al*. (1993) show that new economic information is reflected in a firm's stock price more quickly for firms that are followed by more analysts relative to firms with fewer analysts following them.

4.7. What drives the predictability by international predictors?

The empirical results show that the information on the US market is important for the out-of-sample forecast of New Zealand stock market returns, while that of Australian market is not significant except for small stocks.[15] An interesting question is to ask how this could happen. One possible explanation is the information diffusion hypothesis. Theoretically, the predictability by information diffusion is driven by two factors. The first is the economic links. The larger the magnitude of economic links, the stronger is the predictability. The second is the information friction or the speed of contemporaneous information transfer. We explore these possibilities next.

To investigate the economic link between New Zealand and the other two countries, we follow two ways. Firstly, we examine the relationship of GDP growth rates between New Zealand, US and Australia. Secondly, we analyse the relationship between the GDP growth of New Zealand and the New Zealand export to US and Australia. We use the quarterly seasonal-adjusted GDP growth rate in the analysis.[16]

Panels A, B and C of Table 7 report the results of relationship between the GDP growth rate of New Zealand ($Growth_{NZ}$) and the GDP growth rate of US ($Growth_{US}$) and Australia ($Growth_{AU}$). Panel A reports the results of correlation coefficients. The correlation coefficient between $Growth_{NZ}$ and $Growth_{US}$ is 0.32 and significant at 1 per cent level, while the correlation coefficient between $Growth_{US}$ and $Growth_{AU}$ is 0.27 and significant at 5 per cent level. The link between New Zealand economy and US economy is stronger. In Panel B, we run the regression of $Growth_{NZ}$ on $Growth_{US}$ and $Growth_{AU}$ individually. The adjusted R squares are 8.63 and 6.11 per cent, respectively. The $Growth_{US}$ has higher explanatory power for the GDP growth rate of New Zealand. In Panel C, we run the regression of the $Growth_{NZ}$ on $Growth_{US}$ and $Growth_{AU}$ jointly. If both variables are used as the independent variables, $Growth_{US}$ keeps significant at 5 per cent level, while $Growth_{AU}$ becomes insignificant. This again suggests that the economic link between New Zealand and US is stronger.

Secondly, we analyse the relationship between $Growth_{NZ}$ and US and Australia's shares in New Zealand total exports. Like other small, commodity-producing economies, New Zealand's economic prospects depend greatly on the growth in world trade and output. Both Australia and US are New Zealand's major trading partners. We should observe stronger correlation between the GDP growth rate of New Zealand and the export to that country if the economic link is more relevant. We obtain the quarterly data of New

[15] We thank the anonymous referee for raising such an interesting question.

[16] The GDP data of New Zealand, US and Australia are downloaded from the RBNZ, Federal Reserve at St. Louis and Australian Bureau of Statistics respectively.

Table 7
Economic links between New Zealand, US and Australia

Panel A. Correlation coefficients

Correlation between the GDP growth of New Zealand and US	Correlation between the GDP growth of New Zealand and Australia
0.32[a]	0.27[b]

Panel B. Univariate regression of the GDP growth of New Zealand on the GDP growth rate of US and Australia

	$Growth_{NZ,t} = \alpha_i + \beta_i\ Growth_{i,t} + \varepsilon_{i,t}$		
	α_i	β_i	Adjusted R^2 (%)
i = US	0.46 (3.77)	0.39 (2.89)	8.63
i = AU	0.41 (2.65)	0.36 (2.47)	6.11

Panel C. Bivariate regression of the GDP growth of New Zealand on the GDP growth rate of US and Australia

$Growth_{NZ,t} = \alpha + \beta_1\ Growth_{US,t} + \beta_2\ Growth_{AU,t} + \varepsilon_t$

α	β_1	β_2	Adjusted R^2 (%)
0.30 (1.93)	0.31 (2.19)	0.25 (1.62)	10.52

Table 7 (continued)

Panel D. Correlation between the GDP growth rate of New Zealand and the US and Australia's shares in New Zealand total exports

Correlation between the GDP growth of New Zealand and the US's share in New Zealand total export	Correlation between the GDP growth of New Zealand and the Australia's share in New Zealand total export
0.20[c]	−0.11

This table reports the results of economic links between New Zealand, US and Australia. Panel A reports the correlation coefficients between the GDP growth rate of New Zealand ($Growth_{NZ}$) and the GDP growth rate of US ($Growth_{US}$) and Australia ($Growth_{AU}$). Panel B reports the results of univariate regression of $Growth_{NZ}$ on $Growth_{US}$ and $Growth_{AU}$ individually. Panel C reports the results of bivariate regression of $Growth_{NZ}$ on $Growth_{US}$ and $Growth_{AU}$ jointly. Panel D reports the correlation between $Growth_{NZ}$ and the US and Australia's shares in New Zealand total exports. The numbers in the brackets in Panel B and C are *t*-stats of the parameters.

[a], [b] and [c] denote significance at 1%, 5% and 10% levels, respectively.

Zealand export to US and Australia from Statistics New Zealand and calculate their shares in the total export, respectively. Similar to the results provided by the Ministry of Foreign Affairs and Trade (2013), Australia's share in New Zealand total exports has remained relatively flat between 1992 and 2011. This suggests that although Australia has gone through quite volatile economy cycles during the last 20 years,[17] it does not affect its import from New Zealand and its contribution to the New Zealand economy has been quite stable.

Panel D of Table 7 reports the correlation coefficient between $Growth_{NZ}$ and US and Australia's shares in New Zealand total exports. The correlation between $Growth_{NZ}$ and US's share in New Zealand total export is positive and significant at 10 per cent level, while the correlation between $Growth_{NZ}$ and Australia's share in New Zealand total export is insignificant. This suggests that the economic link between New Zealand and US is more relevant in explaining the change of New Zealand GDP.

We next investigate the speed of contemporaneous information transfer on these markets. We use the excess return of New Zealand stock market (*Exrstock*), US stock market (Exr_{US}), Australian stock market (Exr_{AU}), and VIX in the analysis.[18] We run the Granger causality test to examine which market transfers the information more quickly. Panel A of Table 8 reports the results. The results strongly suggest that both Exr_{US} and VIX Granger cause *Exrstock*, but not vice versa. The US stock and option markets seem to reflect the information more quickly. On the other hand, there is no significant Granger causality effect between *Exrstock* and Exr_{AU}.

Rapach *et al.* (2013) propose a news diffusion model to identify the impact of one leading market to the other market. We employ their model to test the impact of international market on the future change of New Zealand stock market. For the news diffusion from US (Australian) stock market to the New Zealand stock market, we estimate the following model,

$$Exr_{j,t+1} = \beta_{0,j} + \beta_{1,j} Tbill_{j,t} + \beta_{2,j} DivYld_{j,t} + u_{j,t+1}, \tag{19}$$

$$Exrstock_{t+1} = \beta_0 + \beta_1 Tbill_t + \beta_2 DivYld_t + \theta_j \lambda_j u_{j,t+1} + (1-\theta_j)\lambda_j u_{j,t} + u_{NZ,t+1}, \quad j = US, AU, \tag{20}$$

[17] The standard deviation of GDP growth rate of Australia is the highest among the three countries between 1992 and 2011.

[18] Exr_{US} is excess return of S&P500 index, while Exr_{AU} is the excess return of AS31 index.

Table 8
Information spillover between New Zealand, US and Australian market

Panel A. Granger causality

	Hypothesis	Statistics
Exrstock and Exr_{US}	*Exrstock* does not Granger cause Exr_{US}	0.32
	Exr_{US} does not Granger cause *Exrstock*	3.12[b]
Exrstock and VIX	*Exrstock* does not Granger cause VIX	0.94
	VIX does not Granger cause *Exrstock*	4.66[a]
Exrstock and Exr_{AU}	*Exrstock* does not Granger cause Exr_{AU}	0.60
	Exr_{AU} does not Granger cause *Exrstock*	1.33

Panel B. News diffusion from Exr_{US} to *Exrstock*

Model: $Exr_{US,t+1} = \beta_{0,US} + \beta_{1,US}\, Tbill_{US,t} + \beta_{2,US}\, DivYld_{US,t} + u_{US,t+1}$

Specification: $Exrstock_{t+1} = \beta_0 + \beta_1\, Tbill_t + \beta_2\, DivYld_t + \theta_{US}\, \lambda_{US}\, u_{US,t+1} + (1 - \theta_{US})\, \lambda_{US}\, u_{US,t} + u_{NZ,t+1}$

$\beta_{0,US}$	$\beta_{1,US}$	$\beta_{2,US}$	β_0	β_1	β_2	θ_{US}	λ_{US}	$\tilde{\beta}_{US}$
6.71	1.77	1.84	−6.68	−3.37	−2.51	0.84	0.63	0.10
(4.02)	(1.45)	(3.96)	(−7.58)	(−2.85)	(−8.35)	(5.06)	(27.98)	(4.95)

Panel C. News diffusion from VIX to *Exrstock*

Model: $VIX_{t+1} = \beta_{0,VIX} + \beta_{1,VIX}\, VIX_t + \beta_{2,VIX}\, VIX_{t-1} + u_{VIX,t+1}$

Specification: $Exrstock_{t+1} = \beta_0 + \beta_1\, Tbill_t + \beta_2\, DivYld_t + \theta_{VIX}\, \lambda_{VIX}\, u_{VIX,t+1} + (1 - \theta_{VIX})\, \lambda_{VIX}\, u_{VIX,t} + u_{NZ,t+1}$

$\beta_{0,VIX}$	$\beta_{1,VIX}$	$\beta_{2,VIX}$	β_0	β_1	β_2	θ_{VIX}	λ_{VIX}	$\tilde{\beta}_{VIX}$
−5.41	0.93	−0.16	−2.63	−8.55	−1.79	0.72	0.58	0.16
(−16.46)	(36.84)	(−5.40)	(−3.65)	(−5.35)	(−7.89)	(11.47)	(44.01)	(4.57)

Table 8 (continued)

Panel D. News diffusion from Exr_{AU} to $Exrstock$

Model	$Exr_{AU,t+1} = \beta_{0,AU} + \beta_{1,AU}\ Tbill_{AU,t} + \beta_{2,AU}\ DivYld_{AU,t} + u_{AU,t+1}$							
Specification	$Exrstock_{t+1} = \beta_0 + \beta_1\ Tbill_t + \beta_2\ DivYld_t + \theta_{AU}\ \lambda_{AU}\ u_{AU,t+1} + (1-\theta_{AU})\ \lambda_{AU}\ u_{AU,t} + u_{NZ,t+1}$							
$\beta_{0,AU}$	$\beta_{1,AU}$	$\beta_{2,AU}$	β_0	β_1	β_2	θ_{AU}	λ_{AU}	$\tilde{\beta}_{AU}$
4.18	−5.08	−1.56	−2.03	−9.54	−1.68	0.95	0.84	0.04
(3.06)	(−2.64)	(−2.21)	(−1.56)	(−3.73)	(−7.47)	(27.48)	(26.86)	(1.43)

This table reports the results of information spillover between New Zealand stock market (*Exrstock*), US stock market (Exr_{US}), US option market (VIX) and Australian stock market (Exr_{AU}). Panel A reports the results of Granger causality between *Exrstock* and the other three time series. Panels B, C and D report the results of news diffusion model from Exr_{US}, *VIX* and Exr_{AU} to *Exrstock* respectively. The news diffusion parameter $\tilde{\beta}_j$ is calculated by $\left(1-\theta_j\right)\lambda_j, j = US$, *VIX* and *AU* and its standard error is calculated by the delta method. The news diffusion models are estimated by the GMM following Rapach *et al*. (2013). The numbers in the brackets in Panel B, Panel C and Panel D are *t*-stats of the parameters.

[a], [b] and [c] indicate significance at 1%, 5% and 10% levels, respectively.

where $Tbill_{j,t}$ and $DivYld_{j,t}$ are the Treasury bill rate and dividend yield (log) in country j.[19] For the news diffusion from VIX to the New Zealand stock market, we estimate the following model,

$$VIX_{t+1} = \beta_{0,VIX} + \beta_{1,VIX} VIX_t + \beta_{2,VIX} VIX_{t-1} + u_{VIX,t+1}, \tag{21}$$

$$\begin{aligned} Exrstock_{t+1} = \beta_0 + \beta_1 Tbill_t + \beta_2 DivYld_t + \theta_{VIX}\lambda_{VIX}u_{VIX,t+1} \\ + (1-\theta_{VIX})\lambda_{VIX}u_{VIX,t} + u_{NZ,t+1}. \end{aligned} \tag{22}$$

The news diffusion impact from the international market to the New Zealand market is measured by $\tilde{\beta}_j = (1-\theta_j)\lambda_j$, j = US, AU or VIX.

We estimate the parameters of news diffusion models by GMM following Rapach *et al.* (2013). Panel B, Panel C and Panel D of Table 8 report the results of estimation. The standard error of news diffusion parameter $\tilde{\beta}_j$ is calculated using the delta method. The news diffusion parameter from Exr_{US} to *Exrstock* is 0.10 and significant at 1 per cent level. This means one percent shock that happens in US stock market will affect New Zealand stock market by 0.10 per cent in the next month. Similarly, the news diffusion parameter from VIX to *Exrstock* is 0.16 and significant at 1 per cent level. This means one percent shock that happens in S&P option market will affect New Zealand stock market by 0.16 per cent in the next month. These results strongly suggest that US markets transfer the information more quickly than New Zealand stock market. There exists information friction on New Zealand stock market compared with US market. On the other hand, the news diffusion parameter from Exr_{AU} to *Exrstock* is only 0.04 and insignificant. The speed of contemporaneous information transfer on Australian stock market is not significantly faster than New Zealand stock market.

Finally, we follow Hong and Stein (1999) and analyse the cumulative impulse response to the orthogonalised shock in different markets.[20] Figure 2 plots the cumulative impulse response up to lag 12 months between *Exrstock* and Exr_{US} (Panel A) and between *Exrstock* and VIX (Panel B). The impulse response between *Exrstock* and Exr_{US} shows that when the shock happens in New Zealand stock market, its impact on future changes of US stock market

[19] The Treasury bill rate and dividend yield data of US are downloaded from Amit Goyal's website. We thank Guofu Zhou to provide us with the Treasury bill rate and dividend yield data of Australia.

[20] Hong and Stein (1999) show that if information diffuses gradually across the population, the prices underact in the short-run and the momentum traders could profit by trend chasing. However, their attempts at arbitrage will lead to overreaction at long horizons and result in mean reverting.

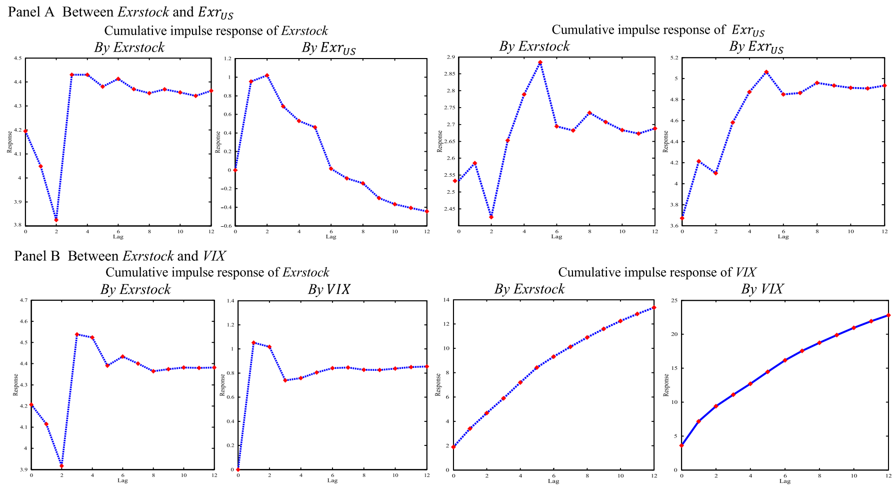

Figure 2 Cumulative impulse response. This figure plots the cumulative impulse response up to lag 12 months between *Exrstock* and Exr_{US} (Panel A), and between *Exrstock* and *VIX*(Panel B).

fluctuates a lot. There is no clear pattern of impact from New Zealand stock market to US stock market. On the other hand, when the shock happens in US stock market, its impact on future change of New Zealand stock market increases first and then decreases. This pattern is close to the pattern reported in Hong and Stein (1999). The impulse response between *Exrstock* and VIX shows similar pattern. These results also support the hypothesis that the information transfers from US market to New Zealand stock market, but not vice versa.

The results in Tables 7 and 8 and Figure 2 show that the predictability of New Zealand stock market returns using US market predictors could be explained by the information diffusion between these two countries. On the other hand, there is no significant information diffusion from Australia to New Zealand. This explains why the predictors from US market and Australian market perform differently in predicting New Zealand stock market returns.

5. Conclusion

This paper studies the impact of international predictors from liquid markets on the predictability of excess returns in the New Zealand stock market using data from May 1992 to February 2011. We use US and Australian stock market return, and VIX as the proxies of international predictors from liquid markets, and test their importance in predicting the excess returns of New Zealand stock market. Many local predictors documented in the literature are also included in the analysis. They are also used to control for the effect of local predictors when testing the significance of international predictors.

US market predictors contribute significantly to the out-of-sample forecasts at short horizons even after controlling for the effect of local predictors. They are robust regardless of whether economic constraints are imposed in the out-of-sample forecast. On the other hand, the contribution of Australian stock market is not significant. These results demonstrate that the diffusion of economic information from US market where price discovery occurs most rapidly is very important for determining future stock returns in the smaller New Zealand market. We also find a significant increase of predictability of New Zealand stock market during the recent financial crisis. The stronger effect of these international factors during the recent financial crisis indicates a contagion effect.

The statistical significance and economic significance in the return predictability of small capitalisation stocks using S&P500 and AS31 are greater than those of large capitalisation stocks. This reflects the higher liquidity, and analyst coverage of the large stocks leads to their quicker price discovery. VIX is more useful for predicting larger capitalisation stocks, which suggests that because these stocks are more globally integrated, market sentiment in the international market has more of an impact on these companies. The investors also tend to trade on the larger and more liquid stocks when there are changes in global risk appetite (Bansal *et al.*, 2011). Additionally, the CP factor that has been shown to be useful for predicting stock returns in the US market is not very useful for the return prediction in the New Zealand market. It does not make a significant contribution to the out-of-sample combination forecast.

In the end, we find that the predictability of New Zealand stock market returns using US market predictors could be explained by the information diffusion between these two countries. This information diffusion is driven by the strong economic link between New Zealand and US, and faster contemporaneous information transfer on US markets. On the other hand, there is no significant information diffusion from Australia to New Zealand. This explains why the predictors from US market and Australian market perform differently in predicting New Zealand stock market returns.

The findings of this research have implications for practitioners and academics. The utility gains coming from the predictive regressions could be used to decide the cost charged to an investor for the access to the information. Predictable variation in stock returns, which is related to the business cycle, is also important for monetary policy decisions. Finally, the evidence of predictable variation in excess returns also has implications for asset pricing models.

References

Ang, A., and G. Bekaert, 2007, Stock return predictability: is it there?, *Review of Financial Studies* 20, 651–707.

Bae, K., A. Karolyi, and R. Stulz, 2003, A new approach to measuring financial market contagion, *Review of Financial Studies* 16, 717–764.

Bansal, N., R. A. Connolly, and C. T. Stivers, 2011, A stock's liquidity and cross-sectional stock dynamics around extreme VIX shocks, Working paper (Saint Louis University).

Bekaert, G., C. Harvey, and A. Ng, 2005, Market integration and contagion, *Journal of Business* 78, 39–69.

Bossaerts, P., and P. Hillion, 1999, Implementing statistical criteria to select return forecasting models: what do we learn?, *Review of Financial Studies* 12, 405–428.

Bowman, R. G., and D. Iverson, 1998, Short-run overreaction in the New Zealand stock market, *Pacific-Basin Finance Journal* 6, 475–491.

Breen, W., L. R. Glosten, and R. Jagannathan, 1989, Economic significance of predictable variation in stock index returns, *Journal of Finance* 44, 1177–1189.

Brennan, M. J., N. Jegadeesh, and B. Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799–824.

Campbell, J. Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

Campbell, J. Y., and R. J. Shiller, 1988, Stock prices, earnings, and expected dividends, *Journal of Finance* 43, 661–676.

Campbell, J. Y., and R. J. Shiller, 1998, Valuation ratios and the long-run stock market outlook, *Journal of Portfolio Management* 24, 11–26.

Campbell, J. Y., and S. Thompson, 2008, Predicting the equity premium out of sample: can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Chen, N., and F. Zhang, 1997, Correlations, trades and stock returns of the Pacific-Basin markets, *Pacific-Basin Finance Journal* 5, 559–577.

Chin, J. Y. F., A. A. Gottesman, and A. K. Prevost, 2002, Contrarian investing in a small capitalization market: evidence from New Zealand, *Financial Review* 37, 421–446.

Cochrane, J., and M. Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160.

Conover, C. M., G. R. Jensen, and R. R. Johnson, 1999, Monetary environments and international stock returns, *Journal of Banking and Finance* 23, 1357–1381.

Dick-Nielsen, J., P. Feldhutter, and D. Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103, 471–492.

Fama, E. F., 1970, Efficient capital markets: a review of theory and empirical work, *Journal of Finance* 25, 383–417.

Fama, E. F., 1981, Stock returns, real activity, inflation, and money, *American Economic Review* 71, 545–565.

Fama, E. F., and K. R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Fama, E. F., and K. R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Fama, E. F., and G. W. Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115–146.

Goetzmann, W. N., and P. Jorion, 1993, Testing the predictive power of dividend yields, *Journal of Finance* 48, 663–679.

Goetzmann, W., J. Ingersoll, M. Spiegel, and I. Welch, 2007, Portfolio performance manipulation and manipulation-proof performance measures, *Review of Financial Studies* 20, 1503–1546.

Goyal, A., and I. Welch, 2003, Predicting the equity premium with dividend ratios, *Management Science* 49, 639–654.
Hansen, P. R., and A. Timmermann, 2011, Choice of sample split in out-of-sample forecast evaluation, Working paper (Stanford University and University of California, San Diego).
Harvey, D., S. Leybourne, and P. Newbold, 1998, Tests for forecast encompassing, *Journal of Business and Economics Statistics* 16, 254–259.
Henkel, S. J., J. S. Martin, and F. Nardari, 2011, Time-varying short-horizon predictability, *Journal of Financial Economics* 99, 560–580.
Hodrick, R. J., 1992, Dividend yields and expected stock returns: alternative procedures for inference and measurement, *Review of Financial Studies* 5, 357–386.
Hong, H., and J. C. Stein, 1999, A unified-theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143–2183.
Jiang, H., A. Habib, and C. Smallman, 2009, The effect of ownership concentration on CEO compensation–firm performance relationship in New Zealand, *Pacific Accounting Review* 21, 104–131.
Johnson, R., and L. Soenen, 2002, Asian economic integration and stock market comovement, *Journal of Financial Research* 25, 141–157.
Kandel, S., and R. F. Stambaugh, 1996, On the predictability of stock returns: an asset allocation perspective, *Journal of Finance* 51, 385–424.
Keim, D. B., and R. F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.
Kong, A., D. E. Rapach, J. K. Strauss, and G. Zhou, 2011, Predicting market components out of sample: asset allocation implications, *Journal of Portfolio Management* 37, 29–41.
Kothari, S. P., and J. Shanken, 1997, Book-to-market, dividend yield, and expected market returns: a time-series analysis, *Journal of Financial Economics* 44, 169–203.
Lally, M., and A. Marsden, 2004, Tax-adjusted market risk premiums in New Zealand: 1931–2002, *Pacific-Basin Finance Journal* 12, 291–310.
Lamont, O., 1998, Earnings and expected returns, *Journal of Finance* 53, 1563–1587.
Leitch, G., and J. E. Tanner, 1991, Economic forecast evaluation: profit versus the conventional error measures, *American Economic Review* 81, 580–590.
Lettau, M., and S. Ludvigson, 2001, Consumption, aggregate wealth and expected stock returns, *Journal of Finance* 56, 815–849.
Lo, A. W., and A. C. MacKinlay, 1990, Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies* 3, 431–467.
Longstaff, F. A., 2010, The subprime credit crisis and contagion in financial markets, *Journal of Financial Economics* 97, 436–450.
Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton, 2011, How sovereign is sovereign credit risk?, *American Economic Journal: Macroeconomics* 3, 75–103.
Marquering, W., and M. Verbeek, 2004, The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39, 407–429.
Ministry of Foreign Affairs and Trade, 2013, New Zealand's trade with Australia, Working paper (New Zealand Ministry of Foreign Affairs and Trade).
Nelson, C. R., 1976, Inflation and the rates of return on common stock, *Journal of Finance* 31, 471–483.
Nelson, C. R., and M. J. Kim, 1993, Predictable stock returns: the role of small sample bias, *Journal of Finance* 48, 641–661.
Pan, J., and K. J. Singleon, 2008, Default and recovery implicit in the term structure of sovereign CDS spreads, *Journal of Finance* 63, 2345–2384.
Pesaran, M. H., and A. Timmermann, 1995, Predictability of stock returns: robustness and economic significance, *Journal of Finance* 50, 1201–1228.

Pinfold, J. F., W. R. Wilson, and Q. Li, 2001, Book-to-market and size as determinants of returns in small illiquid markets: the New Zealand case, *Financial Services Review* 10, 291–302.
Pontiff, J., and L. D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141–160.
Rapach, D. E., and M. E. Wohar, 2006, In-sample vs. out-of-sample tests of stock return predictability in the context of data mining, *Journal of Empirical Finance* 13, 231–247.
Rapach, D. E., J. K. Strauss, and G. Zhou, 2010, Out-of-sample equity premium prediction:combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.
Rapach, D. E., J. K. Strauss, and G. Zhou, 2013, International stock return predictability: what is the role of the United States?, *Journal of Finance* 68, 1633–1663.
Schmeling, M., 2009, Investor sentiment and stock returns: some international evidence, *Journal of Empirical Finance* 16, 394–408.
Stambaugh, R. F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.
Welch, I., and A. Goyal, 2008, A comprehensive look at the empirical performance of equity premium performance, *Review of Financial Studies* 21, 1455–1508.
Xu, Y., 2004, Small levels of predictability and large economic gains, *Journal of Empirical Finance* 11, 247–275.
Zhou, G., 2010, How much stock return predictability can we expect from an asset pricing model?, *Economics Letters* 108, 184–186.

Appendix

This appendix explains how to calculate the aggregate market variables including the dividend-price ratio, the dividend yield, the earnings-to-price ratio, the book-to-market ratio, the pay-out ratio, the return on equity, the debt-to-equity ratio and stock variance.

The aggregate market variables are calculated by taking the average across the individual firms. Figure A1 plots the number of companies with financial statement data available in each year to calculate the aggregate market variables. Price data are available monthly, whereas earnings, dividends, shares outstanding, common equity and debt data are available at annual or semi-

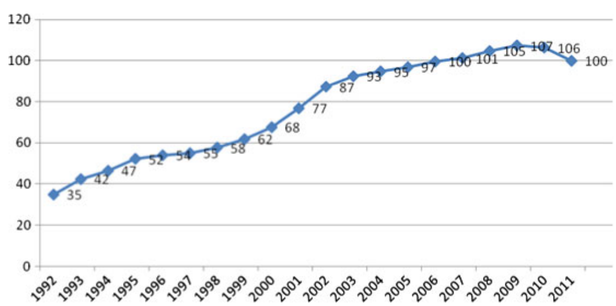

Figure A1 The number of firms with financial statement data available in each year.

annual frequency. The process to get monthly frequency involves separately extrapolating and interpolating the data. Then, the average of the extrapolated and interpolated data for each month is calculated. There is a look-ahead bias when interpolated data are used, whereas the extrapolated data avoid this. The reason for taking the average of these two methods is that in real time although investors only have information available up to the current time, they will have forecasts of the future values of these variables. Therefore, taking the average of the extrapolated and interpolated data incorporates investors' forecasts of the future value of these variables instead of solely relying on past data.