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Intraday return predictability, portfolio maximisation, and hedging

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ABSTRACT

We examine whether intraday Chinese return predictability is linked to optimal portfolio holding and hedging. We find that: (1) S&P500 futures returns only predict Chinese spot market returns in up to 5-minute of trading with predictability disappearing at higher frequencies of trade; (2) the portfolio weight is maximised at the 5-minute trading frequency, when predictability is the strongest; and (3) when predictability is the strongest, significantly less shorting of the futures is required to minimise risk when a long position is taken in the Chinese market.

1. Introduction

Recent years have witnessed a remarkable increase in popularity of stock return predictability. A closer look at this literature suggests that typically the bulk of this literature considers financial ratios (Campbell and Yogo, 2006; Campbell and Thompson, 2008; Welch and Goyal, 2008; Rapach et al., 2010; Westerlund and Narayan, 2012) and, to a lesser extent, macroeconomic indicators (see, for instance, Rapach et al., 2005) as predictors of stock returns. The influence of financial ratios in predicting stock returns is perhaps best demonstrated by the fact that most of the recent econometric advances and methodologies on testing for return predictability have taken financial ratios as predictors in the application of these methods. Lewellen (2004) proposes a bias-adjusted test for the null hypothesis of no predictability; Campbell and Yogo (2006) propose a benforroni-corrected estimator of the null hypothesis of no predictability; Westerlund and Narayan (2012, 2015) propose a generalised least squares estimator that accounts for heteroskedasticity

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of the null hypothesis of no predictability; and Ferreira and Santa-Clara (2011) propose a sum-of-parts method to testing for return predictability.

It is extremely rare to find empirical evidence on other predictors of returns, such as the role of futures markets, despite the fact that the role of futures market as a predictor of the spot market is well developed; see, for instance, Cox (1976) and Hayek (1945). It is equally rare to find empirical evidence on return predictability that utilise intraday data. One can understand why the empirical evidence on return predictability based on intraday data has not progressed. There is simply no intraday data on financial ratio predictors. Surprisingly, while intraday data on exchange rate and short-term interest rate are available, they have not been utilised to examine their power to predict stock returns.

Perhaps the study which uses non-financial ratios as predictors and that comes closest to our study is Rapach et al. (2013). They examine whether the US stock returns can actually predict returns of 11 industrialised countries. Using monthly data over the period 1980 to 2010, they find strong evidence (both in-sample and out-of-sample) that the US stock returns actually predict returns of industrialised countries. On the basis of this finding they claim that: "Specifically, one cannot simply apply an analogous version of a US asset pricing model based on economic variables to another country; instead, our results call for an international asset pricing model that explicitly incorporates the leading role of the US" (Rapach et al., 2013: page 4).

These findings of Rapach et al. (2013) have three implications for our research. First, Rapach et al. (2013) claim that "[t]he predictive ability of lagged US returns is not only an interesting empirical fact with implications for international hedging and investing, but it also has important implications for asset pricing models", however, they do not show whether hedging strategies can be successful. We do. We show not only how investors can take hedging positions but also show how portfolio weights of an investor intending to invest in the US and Chinese stock markets can be maximised.

Second, Rapach et al. (2013) use the US spot stock returns as a predictor and find predictability. However, it is now a stylised fact, that it is the futures market which leads the price discovery. Therefore, the question is: Can the futures (US) market predict the Chinese spot market? Third, it is true that the US market leads the global markets and this is further confirmed by Rapach et al. (2013). However, their empirical evidence is based only on low frequency (monthly) data. The resulting question that stands tall and deserves particular attention is: Does the US market still predict international country stock returns in high frequency data? We answer these questions using intraday data, which is not a trivial issue. A large literature in financial economics shows that the information content in intraday data is relatively high which is an asset and ignoring it can be costly in practice (see, *inter alia*, Bollerslev and Wright, 2001). We use not the US spot returns, but S&P500 futures returns for the simple reason that it is the futures market which dominates the price discovery process, as we discuss in detail later; therefore, it is likely to contain more information that can aid predictability.

On the whole, our paper should be seen as extending the work of Rapach et al. (2013) in terms of trying to understand the role of the US stock market in a global context; that is, whether or not it leads other markets. However, there are two important differences between our work and that of Rapach et al. (2013). First, our empirical evidence is based on intraday data, which is relatively rich. Second, we examine the international leadership role of the US stock market but not based on the spot market; rather, we use futures market returns as a predictor, which is most likely to have a richer information content. This is not the only thing we contribute. We are also interested in understanding whether there is a link between return predictability, portfolio weight optimisation, and hedging, and this is not a trivial issue. To our knowledge, this link has not been explored previously although Rapach et al. (2013) argue in favour of such a link as highlighted earlier. We discuss the importance of understanding this link in the next section.

Our results offer several fresh insights. First, while we do find that the US market (S&P500 returns) predicts the Chinese stock market (Shanghai stock exchange), this evidence is trading frequency dependent. Strong evidence (both in-sample and out-of-sample) of predictability is found at the 5-minute trading frequency. Second, evidence of predictability is associated with portfolio allocation; that is, when predictability is the strongest (at the 5-minute trading frequency), investment in the Chinese spot market is maximised. Third, we discover a relationship between predictability and hedging. When predictability is strongest, the need to take a short position in the S&P500 is minimised. Finally, in an economic significance analysis we not only find that the portfolio variance is reduced most when predictability is the strongest but strong predictability is also associated with the highest investor utility.

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2. Empirical framework and motivation

In this section, we deal with two things. First, we explain the predictive regression model that we use to test whether S&P500 futures returns predict Chinese stock market returns. Second, we explain the motivation for our proposed predictive regression framework.

2.1. Predictive regression model

Our predictive regression framework, based on a generalised autoregressive conditional heteroskedasticity (GARCH) model, follows two leads. First, it is not uncommon to utilise a GARCH-based predictive regression model. In this regard, our model is consistent with Marquering and Verbeek (2004). Second, as we will show in the next section, our predictive regression model is not immune to heteroskedasticity. In light of this, a GARCH model or a GARCH-type model, as suggested by Westerlund and Narayan (2012), is most suitable. Therefore, we have the following GARCH (p,q) predictive regression model:

$$\boxed{R_t^C = \alpha_0 + \beta_1 R_{t-1}^{US} + \varepsilon_t} \tag{1}$$

where R_t^C is the returns on the Chinese stocks, computed as $\log(P_t^C/P_{t-1}^C)*100$, with P being the price index; R_t^{US} is the returns on the S&P500 price index, computed as returns $\log(P_t^{US}/P_{t-1}^{US})*100$; and the conditional variance, say σ_t^2, is represented as a linear function of its past values and lagged squared innovations resulting from the mean equation. This can be specified as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t\text{-}j}^2 \tag{2}$$

where $\alpha_0 > 0$, $\alpha_i \geq 0 \, \forall \, i$, $\beta_j \geq 0 \, \forall \, j$, and the characteristic roots of $(1 - \sum \alpha_i - \sum \beta_j)$ lie outside the unit circle. We use the Schwarz Information Criteria to select the optimal lag orders of the GARCH model.

2.2. Motivation 1: why do the US futures market matter?

Hypothesis 1. That the S&P500 futures returns predict Chinese spot market returns.

There are two aspects of the predictor model that needs some discussion. First, what is the relevance of the futures predictor? The futures prices have a tendency to adjust to new information instantaneously. By comparison, Chan (1992); Kawaller et al. (1987), and Stoll and Whaley (1990) contend that many of the component stocks in any given index are not traded frequently enough to allow prices to update to information rapidly. Generally, the average time between trades for component stocks in the market index is longer compared to futures market (see Abhyankar, 1995). Futures markets, because the cost of taking a position in the stock index futures is lower than taking positions in stocks, are more attractive for informed traders (see Fleming et al., 1996 and Kim et al., 1999). As a result, informed traders are likely to trade more in the stock index futures and, therefore, price movements in stock index futures adjust before the price movements on stocks. Chan (1992) and Diamond and Verrecchia (1987) argue that one other difference between stock and futures markets is the constraints on short-selling. While short-selling is restricted in the cash market in the futures market there is no such constraint. For these same reasons, price discovery is also dominated by the futures market. Therefore, several studies examine the temporal relationship between spot and futures markets, documenting strong evidence that futures returns significantly lead stock market returns; see, for instance, Kawaller et al. (1987); Stoll and Whaley (1990).

Second, why does the US futures market matter for Chinese stock market returns? It is now well recognised, at least empirically, that the US equity market leads international markets. The leadership role of the US market has been demonstrated through various ways. Rapach et al. (2013) use predictive regression models; they examine whether the US spot market returns can predict stock returns of 11 industrialised countries'. They find strong evidence that the US market returns are a successful predictor of international returns. Goh et al. (2013) examine, using monthly data over the period 1993 to 2008, whether or not the US economic variables predict Chinese stock market returns. They find that following China's accession to the World Trade Organisation (post-2002), which led to greater integration of the Chinese economy with the rest of the world, the US economic variables show strong evidence of both in-sample and out-of-sample predictability. These authors, as a result, claim that: "… investors interested in investing in the Chinese stock market should pay attention to both the US and China economic variables". From the extant literature we learn that the US economy is important for predicting Chinese stock market. Therefore, our focus on the S&P500 futures market is not only justified but timely.

Based on these discussions, our first hypothesis is that the S&P500 futures returns predict Chinese spot market returns.

2.3. Motivation 2: what is the link between return predictability, portfolio weights, and hedging?

Hypothesis 2a. Return predictability leads to greater weight in the predictable asset.

Predictability and portfolio weights have a long history rooted in the work of Markowitz (1952). In fact, the mean–variance utility function links profit maximisation to the weight of the risky asset in a portfolio. The key point is that if one is able to predict returns from a particular asset in a portfolio then the weight attached to this asset will be higher holding all other things, such as portfolio variance and risk aversion, constant. Therefore, we expect the portfolio weight in Chinese stocks to be higher at trading frequencies at which Chinese returns can be predicted compared to trading frequencies at which there is no predictability.

Hypothesis 2b. Return predictability leads to less need for hedging in order to minimise risk.

If an investor is able to predict returns of a particular stock then this should minimise the need for short-selling. Predictability of a stock's return suggests that investors can decide with greater precision on the amount of short-selling to be undertaken. On the other hand, if a stock return is unpredictable, an investor will have to take a strong short-selling position in order to cover for the risk of a fall in price of the unpredictable stock.

3. Data and results

In this section, we do two things. First, we describe the data set. We undertake a preliminary analysis of the data set to understand its key features. Second, we present and discuss the results. The results are divided into four parts. In the first part, we examine in-sample predictability, testing whether S&P500 futures returns predict Chinese stock market returns. In the second part, we examine whether predictability holds using an out-of-sample forecasting exercise. In the third part, we examine portfolio maximisation and hedging and make the link with predictability at different trading frequencies. In the final part, we undertake an economic significance analysis.

3.1. Preliminary analysis of the data

We have a rich data set; we use intraday data on 150 Chinese (Shanghai stock exchange) stock returns (value-weighted) for which consistent time-series intraday data are available. We take this data series from Narayan et al. (2015: pp. 139–140), who provide further details on this data. The S&P500 futures returns (computed using the prices of nearby S&P 500 futures contracts) are used to proxy activities in the US futures market. The sample period we consider is from 2 January 2008 to 30 July 2010. The sample is motivated by availability of intraday data on China.[1] The Chinese intraday stock price data (A-shares) were obtained from the China Securities Markets and Accounting Research (CSMAR) while the S&P500 futures price data was obtained from SIRCA. We then merged the China and S&P500 price series. In doing so, we only kept observations for those times that were common to both data sets. Let us consider

[1] We also estimated all results by excluding the period characterised by the global financial crisis. The results are very similar and do not change our main conclusions. Therefore, we do not report these sub-sampled results in the paper. Detailed results are available upon request.

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an example of the time between 9.30 am to 9.40 am. If we had spot price data at 9:30, 9:35, 9:36 (am) for China and we had S&P500 futures data at 9:30, 9:31, 9:32, 9:33, 9:34, 9:35, 9:36, 9:37 (am), we kept only the data for 9:30, 9:35, and 9:36 (am). From this, we create the data set at the 1-minute, 5-minute, 10-minute, 30-minute, 60-minute, 90-minute, and 120-minute frequencies. This means that after cleaning this data we end up with data for both countries on the same day at the same time intervals.

Since China is 13 h ahead of US, when we lag the S&P500 futures returns by one period, we capture lagged futures returns equivalent to 11 h. Indeed in additional tests, we estimated the predictive regression model using a two-period lag of the futures return. This is equivalent to capturing 35 h of lagged information on the futures. Since the results are qualitatively similar to those obtained when using the one-period lagged futures returns, we only report results from this model.

In the literature on predictability, no attempt has been made to study whether or not the US futures market leads international markets. Because we do so in this paper, at this stage it is appropriate to provide the rationale for using intraday data as opposed to low frequency data, as used by Rapach et al. (2013) for instance. Our motivation for using intraday data has roots in country-specific studies where emphasis has been on testing whether futures market predicts the cash market. This literature has found that while it is true that the futures market predicts the cash market returns, this predictability is very much time-dependent; in other words, this predictability is restricted to specific trading frequency. Let us consider these examples more closely. Kawaller et al. (1987), for instance, find that S&P500 futures prices predict cash prices but only between 20 and 45 times of trading. Stoll and Whaley (1990) document that the S&P500 and Major Market Index futures predict stock index returns by about 5 min on average. The question emanating from these findings is: Does the S&P500 futures returns predict the Chinese stock returns up to any specific trading frequency or does predictability hold throughout the day?

Before we answer this question, we examine some simple statistical features of the data set. Since this is the first attempt to connect intraday Chinese data with S&P500, understanding the data set is important. We begin by discussing the correlation coefficients of Chinese and S&P500 returns together with their covariance for each of the seven trading frequencies. First, correlation of Chinese returns with S&P500 returns is weakest at the highest frequencies of trade. For example, at the 1-minute frequency of trade, the correlation is not only negative it is statistically insignificant. Moreover, while at the 5-minute and 10-minute frequencies of trading the correlation coefficient becomes positive, the null hypothesis that it is equal to zero cannot be rejected even at the 10% level of significance. The correlations are low at less than 0.009. From 30-minute trade to 120-minute trade the null that the correlations are zero is rejected at least at the 5% level of significance and the correlations are relatively strong over these trading frequencies. The range of correlations over these frequencies is 0.06 to 0.10. Second, we also notice that the covariance between the two returns increased substantially; while in less than 30-minute trading the covariance was less than 0.06, in the post-30 minute trading the covariance was in the 0.42 to 1.29 range.

In Table 1, we report the autocorrelation coefficients of the Chinese stock market returns and the S&P500 returns for up to six lags. A number of features of the data can be read by simply looking at the autocorrelation functions of the two return series. Consider the Chinese return series. The first observation is that at the first lag the autocorrelations are negative and relatively high. The null hypothesis that there is no autocorrelation, based on the Ljung–Box Q-statistic, is strongly rejected at all frequencies except at the 90-minute trading. The autocorrelation is in excess of 0.44 for 1-minute, 10-minute, 60-minute, and 120-minute trading. This suggests that for these four trading frequencies, in comparison with other trading frequencies, a significant number of trades in one direction is followed by further trading activity in the same direction on the Chinese stock exchange. The second observation is that the autocorrelations decay fairly rapidly at all frequencies. When we consider the S&P500, by comparison, two differences are observed: (a) the null of no autocorrelation at all lags is rejected strongly only in 1-minute, 5-minute, and 10-minute trading; and (b) the autocorrelation coefficients are relatively small and are maximised at the 1-minute of trading with one lag, suggesting that around 22.7% of trades follow the same direction. Finally, like with the Chinese stock returns, the decay in autocorrelations in S&P500 futures returns is rapid.

3.2. Intraday evidence of predictability

In Table 3 we report in-sample and out-of-sample evidence on predictability of the Chinese stock returns at seven different frequencies. Reading the results from the in-sample test, we find that while the null

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Table 1
Autocorrelation (1–6 lags).
This table is about autocorrelations. The autocorrelations are reported at lags 1 to 6. The null hypothesis that there is no autocorrelation, and is tested using Ljung–Box Q-statistic. The asterisk is used to denote the rejection level of the null hypothesis with ** (***) denoting rejection at the 5% and 1% levels, respectively. The results are reported at all seven trading frequencies. Panel A contains results for the returns on the Chinese stock market and panel B contains results for the returns on the S&P500 stock index. The last row contains the number of observations at each frequency of trade.

	1 min	5 min	10 min	30 min	60 min	90 min	120 min
Panel A: China. Lag							
1	−0.4430***	−0.114***	−0.4660***	−0.0450***	−0.4550***	−0.0330	−0.486***
2	−0.0110***	0.005***	−0.0020***	0.0010***	0.0080***	0.049**	−0.001***
3	−0.0070***	−0.04***	0.0030***	0.0310***	0.0120***	−0.027**	0.000***
4	−0.0030***	−0.004***	−0.0020***	0.0240***	−0.0110***	0.002**	−0.003***
5	−0.0010***	0.0000***	0.0000***	0.0060***	−0.0120***	−0.086***	−0.119***
6	0.0000***	0.004***	0.0010***	0.0210***	0.0030***	0.044***	0.238***
Panel B: S&P500. Lag							
1	−0.2270***	−0.11***	−0.069***	0.009	0.011	0.016	0.012
2	−0.0180***	−0.011***	0.006***	0.017	0.014	−0.008	−0.08**
3	−0.0050***	0.001***	0.017***	−0.004	−0.013	0.012	−0.033**
4	−0.0100***	0.006***	0.018***	0.007	−0.04	−0.005	−0.084***
5	0.0000***	0.005***	−0.001***	0.012	−0.037	−0.054	0.006***
6	0.0020***	0.015***	−0.01***	−0.01	0.003	−0.018	0.008**
No. of observations	242,952	49,128	24,900	4631	2262	2253	1079

hypothesis of no predictability is comfortably rejected at the 5% level or better in the case of 1-minute, 5-minute, 90-minute, and 120-minute Chinese returns, the null is not rejected at the 10-minute, 30-minute, and 60-minute returns. Therefore, we observe Chinese return predictability only during the highest frequencies of trade. One issue that biases our results, however, is the potential endogeneity. We care for the fact that the predictor variable in our predictive regression model may well be endogenous. If this is the case then our inference on the no predictability null is likely to be spurious. We, therefore, address this issue. We first test for endogeneity of the predictor variable. We simply regress the innovations from the predictive regression model, say (e_t^1) against residuals from a first-order autoregressive model of the predictor variable, say (e_t^2). The model takes the following form:

$$e_t^1 = \alpha_0 + \alpha_1 e_t^2 + \mu_t. \tag{3}$$

We then test the null hypothesis that $\alpha_1 = 0$; if the null is rejected then this is evidence in favour of an endogenous predictor variable. The results reported in the last column of Panel B (Table 2) suggest that endogeneity is not a problem for predictive regression models estimated at the 1-minute to 10-minute frequencies but it is an issue for the rest of the data frequencies. We, therefore, estimate a VAR-based predictive regression model. We use the Schwarz Information Criterion to obtain the optimal lag length of the VAR model, which is then utilised in the estimation. The lag lengths are reported in Panel B of Table 3. From the VAR model our main interests are on two sets of results: (i) the one period lag of the predictor variable; and (ii) the joint significance of all lags of the predictor variable. This approach is common in VAR-based predictive regression models; for a recent application, which motivates us for the present analysis, see Tetlock (2007). We report these results in Table 3 (Panel B). The results, obtained using Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to q lags (which are reported in the first column of the table in square brackets) are as follows. Based on the one-period lagged predictor variable, the null of no predictability is only rejected at the 10% level for the model estimated using the 30-minute frequency of data. Meanwhile, the joint F-test reveals that the null hypothesis can be rejected at the 10% level in the case of the 30-minute model, at the 5% level in the case of the 90-minute model and at the 1% level in the case of 1-minute, 5-minute, and 10-minute models. For the remaining two models (60-minute and 120-minute), there is no evidence of any predictability.

Table 2
Selected descriptive statistics of the data.
This table is about the data. A snapshot, represented by selected descriptive statistics—namely, means, standard deviation (SD), skewness, kurtosis, persistency, and heteroskedasticity—is presented. Persistency of the Chinese stock returns and the S&P500 returns is estimated through a first-order autoregressive (AR(1)) model. The AR(1) coefficient is reported together, in parenthesis, with the p-value testing the null that the coefficient is zero. Heteroskedasticity is computed by running an AR(12) model of returns and subjecting the residuals to a autoregressive conditional heteroskedasticity (ARCH) test at lags of six and 24. The ARCH test is a Lagrange Multiplier-based test which examines the null hypothesis of no ARCH. The p-values associated with testing the null hypothesis are reported in parenthesis.

Panel A: China	Mean	SD	Skewness	Kurtosis	AR(1)	ARCH(6)	ARCH(24)
1-minute	−0.00004	1.0965	0.0142	5244	−0.4431	27,403	7368
					(0.0000)	(0.0000)	(0.0000)
5-minute	−0.0002	0.3619	0.8235	283.069	−0.1141	684.68	234.967
					(0.0000)	(0.0000)	(0.0000)
10-minute	−0.0004	1.6389	0.1729	1621	−0.4658	3085	928.75
					(0.0000)	(0.0000)	(0.0000)
30-minute	−0.0019	1.0529	−0.4371	25.9783	−0.0451	152.57	38.857
					(0.0021)	(0.0000)	(0.0000)
60-minute	−0.0046	4.6588	−0.2176	200.17	−0.4547	272.37	105.26
					(0.0000)	(0.0000)	(0.0000)
90-minute	−0.0044	1.5517	−0.1619	14.0521	−0.0332	52.4311	16.7933
					(0.1155)	(0.0000)	(0.0000)
120-minute	−0.0107	14.1456	0.0319	50.824	−0.4863	165.557	76.9572
					(0.000)	(0.000)	(0.000)

Panel B: S&P500	Mean	SD	Skewness	Kurtosis	AR(1)	ARCH(6)	ARCH(24)	Endogeneity
1-minute	−0.0001	0.1344	−0.5004	80.362	−0.2265	329.35	118.22	−0.0069
					(0.0000)	(0.0000)	(0.0000)	(0.6834)
5-minute	−0.0006	0.2348	−0.5913	47.3598	−0.1098	224.91	66.849	0.0018
					(0.0000)	(0.0000)	(0.0000)	(0.7963)
10-minute	−0.0012	0.31	−0.3747	29.9751	−0.0688	133.28	38.3345	0.0469
					(0.0000)	(0.0000)	(0.0000)	(0.1625)
30-minute	−0.0061	0.7055	−1.6004	52.672	0.0095	3.2611	6.4312	0.1289
					(0.5202)	(0.0034)	(0.0000)	(0.0000)
60-minute	−0.0127	1.0337	−0.3366	31.4026	0.0111	13.0594	22.1892	0.3935
					(0.5972)	(0.0000)	(0.0000)	(0.0000)
90-minute	−0.0125	1.0126	−1.0315	26.7853	0.0164	7.6744	9.5822	0.1649
					(0.4377)	(0.0000)	(0.0000)	(0.0000)
120-minute	−0.0268	1.5071	−0.0803	23.4627	0.0122	11.7347	9.1968	0.5733
					(0.6888)	(0.000)	(0.000)	(0.0448)

The out-of-sample predictability evidence is based on three statistics: the out-of-sample R-squared (R^2), the relative Theil U (RTU) statistics, and the mean squared forecast error (MSFE) adjusted (MSFE-A) test. The R^2 was proposed by Campbell and Thompson (2008) and is:

$$R^2 = 1 - \frac{MSE_{model}}{MSE_{mean}} \tag{4}$$

where MSE_{model} is the mean square error of the out-of-sample predictions from our proposed model, while MSE_{mean} is the mean squared error of the historical sample mean. When $R^2 > 0$, our proposed predictive regression model predicts returns better than the historical mean, and *vice versa*. By comparison, the RTU statistic is defined as the ratio of the TU from the predictive regression model relative to the historical average. If the RTU < 1, our proposed predictive regression model outperforms the historical average. Finally, the MSFE-A test statistic was proposed by Clark and West (2007). It examines the null hypothesis that the historical average MSFE is less than or equal to the MSFE from the proposed predictive regression model against the one-sided (upper-tail) alternative hypothesis that the historical average forecast MSFE is greater than the MSFE from the proposed predictive regression model.

The out-of-sample predictability evidence based on the GARCH model, reported in the last column of Table 3 corroborates the in-sample results in that evidence of out-of-sample predictability is found both at 1-minute and 5-minute frequencies of trade as well as at the 120-minute of trade. We consider the

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Table 3
In-sample and out-of-sample evidence on predictability.
This table contains both in-sample (column 2) and out-of-sample (column 3) evidence on return predictability. The results include those based on a GARCH predictive regression model (Panel A) and a VAR-based predictive regression model (Panel B). Panel A: For the in-sample evidence, we report the null hypothesis that S&P500 returns do not predict the Chinese stock market returns. The t-statistics are reported to judge the null hypothesis. In the last column, the out-of-sample evidence is reported based on two test statistics: (i) the relative Theil U statistic (RTU) and the out-of-sample R^2. The RTU statistic is defined as the ratio of the Theil U statistic from the predictive regression model relative to the historical average. If the RTU <1, our proposed predictive regression model outperforms the historical average. The R^2 is computed as the one less the ratio of mean squared error (MSE) from the predictive regression model to the MSE from the constant returns model. If the R^2>0, it suggests that the predictive regression model outperforms the historical average. The MSEF-A test examines the null hypothesis that the historical average MSFE is less than or equal to the MSFE from the proposed predictive regression model against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than the MSFE from the proposed predictive regression model. Panel B: The t-test statistic related to beta simply tests the null hypothesis of no predictability based on the one period lagged predictor variable, while the joint F-test simply refers to the joint null hypothesis that all lags of the predictor variables is equal to zero. The out-of-sample test statistics take as benchmark a model where all lags of predictor variable are set to zero—therefore, this is a restricted model containing only a constant term and lags of the dependent variable (Chinese stock returns). The square brackets appearing in the first column represent the optimal lag lengths obtained using the Schwarz Information Criterion. * (**) *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: GARCH-based evidence

	In-sample		Out-of-sample		
	Beta	t-Statistic	RTU	R^2	MSFE-A
1-minute	−0.0776***	−4.6791	1.000425	0.000962	1.96**
5-minute	0.0146**	1.9757	0.99774	0	2.35***
10-minute	0.0314	0.3675	0.996421	0	1.68**
30-minute	0.0319	1.6186	0.987214	−0.00031	1.15
60-minute	0.0196	0.5617	0.999127	0.000251	1.88**
90-minute	0.0772**	2.4802	1.001854	−0.00047	0.77
120-minute	−0.2569***	−2.798	0.998199	−0.00094	1.46*

Panel B: VAR based evidence

	In-sample		Out-of-sample		
	Beta, t-test	Joint F-test, p-value	RTU	R^2	MSFE-A
1-minute [32]	−1.4269	0.0000***	0.9067	0.0005	1.89**
5-minute [20]	−0.1501	0.0000***	0.9827	0.000009	2.39***
10-minute[10]	1.5659	0.0000***	1.0348	0.00007	1.91**
30-minute [1]	1.8894*	0.0584*	1.0669	0.0016	1.62**
60-minute [1]	0.0004	0.9792	1.0314	−0.0001	1.11
90-minute [5]	1.3342	0.0403**	1.7174	−0.0008	0.66
120-minute [5]	0.1618	0.9330	1.3205	0.0013	1.72**

5-minute trading to have the strongest predictability compared to 1-minute trade because unlike the 1-minute trade all three out-of-sample techniques suggest predictability at the 5-minute trading frequency.

Reading evidence obtained from the VAR predictive regression model, we note the following. There is no out-of-sample evidence of predictability for 60-minute and 90-minute trading frequencies: for the 60-minute and 90-minute trading model, none of the test statistics suggest any predictability. For the 10-minute model, only two of the three test statistics support out-of-sample predictability, while for the 30-minute trade evidence is weaker with support from only one of the procedures. In summary, the evidence of predictability, in particular for models estimated at the 10-minute, 30-minute, 60-minute, and 90-minute trading frequencies is weak. In addition, in out-of-sample evaluations, all three test statistics suggest that the predictive regression model beats the restricted model for 1-minute and 5-minute predictions. Strictly speaking, then, we can confidently claim that the S&P500 futures returns predict Chinese stock returns strongly at both the 1-minute and 5-minute trading.

3.3. Intraday trend in portfolio choice and hedging

In the previous section, we discovered that the S&P500 returns have predictive power in that it can predict Chinese stock returns. However, this predictability is dependent on the trading frequency interval. Strictly

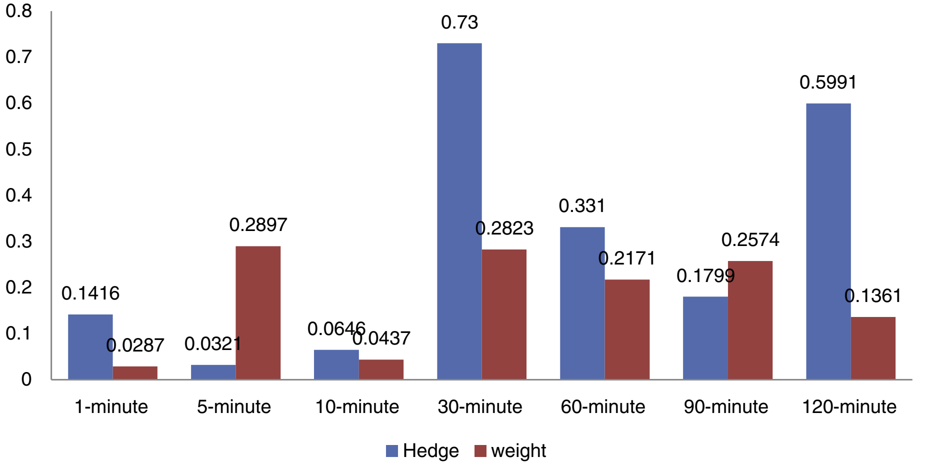

Fig. 1. Intraday portfolio weights and hedge ratios. This figure plots the portfolio weights and the hedge ratios at each of the seven trading frequencies. The portfolio weights represent the amount of investment that goes into the Chinese spot market in a one dollar portfolio. The hedge ratio suggests the shorting position for an investor.

speaking, if one took evidence from both in-sample and out-of-sample analysis, it is clear that predictability only exists at the 1-minute and 5-minute trading, with it being statistically strong for the 5-minute model. What is the implication of the evidence on intraday predictability? Using returns data at all frequencies, we estimate a bivariate GARCH(1,1) model. Our aim is to examine for an investor, who has only these two assets (S&P500 and the Chinese stocks) in her portfolio, (i) the optimal portfolio allocation and (ii) the hedging position.[2]

To achieve the first aim, we follow Kroner and Ng (1998) and obtain a portfolio that minimises risk without reducing expected returns. The weight (w_t) of the Chinese spot (C) market in a one dollar portfolio of Chinese spot and S&P500 futures (US) at time t is given by:

$$w_t = \frac{h_t^{US} - h_t^{C,US}}{h_t^C - 2h_t^{C,US} + h_t^{US}}. \tag{5}$$

The time-varying conditional variance of the spot market (h_t^C) and the S&P500 futures (h_t^{US}), and the conditional covariance ($h_t^{C,US}$) are extracted from estimating a bivariate GARCH model similar to the one proposed by Baillie and Myers (1991). The model's innovations, say $\{e_t\}_{t=1}^T = \{e_t^{US}\}_{t=1}^T + \{e_t^C\}_{t=1}^T$ where superscript C and US represent innovations resulting from the spot and futures error correction equations, respectively, are modelled as:

$$e_t|\Omega_{t-1} \sim N(0, h_t), h_t = \begin{bmatrix} h_t^C & h_t^{US} \\ h_t^{US} & h_t^{C,US} \end{bmatrix} \tag{6}$$

$$\text{vec}(h_t) = C + A\,\text{vec}(e_{t-1}e_{t-1}') + B\,\text{vec}(h_{t-1}) \tag{7}$$

From here, the conditional minimum variance hedge ratio, say R^*, at time t is simply $h_t^{C,US}/h_t^C$.

Beginning with the portfolio weights this is what we find — see Fig. 1. In a $100 dollar portfolio of Chinese spot and S&P500 futures, the portfolio weight of Chinese stocks varies from $2.87 cents (1-minute trade) to $28.97 (5-minute trade). The average portfolio weight across all seven trading frequencies is $17.93 and

[2] In recent times there has been a surge in interest on hedging strategies more generally. For studies on hedging in other context, see Arouri et al. (2015); Chuang et al. (2014); Carfi and Musolino (2014); Fu et al. (2012); Lin et al. (2014); Beckmann et al. (2015); Reboredo and Rivera-Castro (2014); and Hoang et al. (2016).

the weight is maximised at the 5-minute trade. Interestingly, the 5-minute frequency is one where strongest evidence of both in-sample and out-of-sample predictability was found.

The hedge ratios fall in the range of 0.03 (5-minute) to 0.73 (30-minute). This implies that in order to minimise risk for short hedgers at the 30-minute trade, a $100 long (buy) in the Chinese market is shorted (sold) by $73 of the S&P500 futures. By comparison, at the 5-minute trade, significantly less shorting of the futures is required to minimise risk when a $100 long position is taken in the Chinese market.

3.4. Economic significance analysis

We reach this section with two clear messages: first, that the S&P500 futures returns predict Chinese stock returns but this predictability is limited to only the early part of the day's trading; and, second, evidence of predictability, particularly at the 5-minute horizon, is associated not only with a maximisation of portfolio weight in the Chinese stocks but also the need to hedge in order to minimise risk in the Chinese market is the lowest. We now turn to investigate whether there are economic gains to be made from the hedging position established earlier. Our approach here is twofold. First, we estimate the reduction in variance, which is simply the difference in variance from a hedged portfolio (HP) and an unhedged portfolio (UP). If this difference is positive then this suggests that hedging in the Chinese market is effective. Following Ederington (1979), the variance of the hedged portfolio can be obtained as:

$$Var(HP_t|\Omega_{t-1}) = var\left(\left(R_t^C - H^* R_t^{US}|\Omega_{t-1}\right)\right). \tag{8}$$

And the variance of the unhedged portfolio is obtained by simply setting the hedge ratio to zero, in which case we obtained:

$$Var(UP_t|\Omega_{t-1}) = var\left(\left(R_t^C|\Omega_{t-1}\right)\right). \tag{9}$$

Our second approach is utility function-based in that it takes into account the risk and return of the hedged portfolio, following closely the work of Kroner and Sultan (1993). This model assumes a mean–variance investor with the following utility function:

$$E[U(HP_t|\Omega_{t-1})] = E(HP_t|\Omega_{t-1}) - \gamma Var(HP_t|\Omega_{t-1}) - TC \tag{10}$$

where γ represents the investor's risk aversion parameter and in order to gauge the robustness of the results we use different levels of γ and TC is the transaction cost which we set to 0.05%. Similarly, the expected utility is computed from the unhedged portfolio. It follows that the expected utility gain (UG) can simply be computed as follows:

$$UG = E[U(HP_t|\Omega_{t-1})] - E[U(UP_t|\Omega_{t-1})]. \tag{11}$$

The results on variance reduction and utility gains are reported in Table 4. The results are reported for each of the trading frequencies. Two results are of importance here. First, on variance reduction we find that the largest reduction in variance is obtained at the 5-minute trading frequency. Variance is reduced by 52.5% if an investor is following a hedged portfolio compared to an unhedged portfolio. This result is consistent with earlier results at the 5-minute trading frequency. Earlier results, for instance, suggested that at the 5-minute trading frequency predictability was the strongest, portfolio weight in Chinese stocks was maximised, and hedgers required the lowest amount of shorting of the S&P500 futures to minimise risk. Moreover, we notice that variance reduction from a hedged portfolio is also possible at other trading frequencies where in-sample tests suggested return predictability. For instance, at the 90-minute and 120-minute trading, a reduction in variance from a hedged portfolio of 4.4% and 0.002%, respectively, is achieved, although the magnitude of variance reduction is a very small fraction of variance reduction obtained when predictability is the strongest (at the 5-min trading). Second, we read results on utility gains. The main finding here is that at trading frequencies where in-sample evidence of predictability was found evidence of utility gains are observed and these gains are the highest in the post-60 min trading intervals.

Table 4
Economic significance results.
This table contains two sets of results. In column 2, the percentage reduction in variance, which is simply the difference between the variances of hedged and unhedged portfolios. A positive value, therefore, represents the percentage reduction. The second set of results, presented in column 3, is about utility gains. Utilities are a positive function of the mean portfolio and a negative function of portfolio variance (which is a multiple of the risk aversion parameter) and transaction cost. The difference between the hedged portfolio utility and unhedged portfolio utility, therefore, represents the utility gain. The utility gain takes into consideration a range of risk aversion parameters that reflect a low risk ($\gamma=3$), medium risk ($\gamma=6$) , and high risk investor ($\gamma=12$).

Trading frequency	Variance reduction (%)	Utility gains		
		$\gamma=3$	$\gamma=6$	$\gamma=12$
1-minute	−0.5649	0.0000	0.0000	−0.0001
5-minute	52.5218	0.0003	0.0006	0.0012
10-minute	0.0441	0.0001	0.0002	0.0004
30-minute	−10.836	−0.0005	−0.0129	−0.0290
60-minute	1.6834	0.0103	0.0186	0.0353
90-minute	4.3866	0.0022	0.0033	0.0055
120-minute	0.0017	0.0333	0.0543	0.0961

4. Concluding remarks

In this paper we identify specific hypotheses relating to predictability, portfolio optimisation, and hedging in a portfolio containing two assets, the Chinese spot market and the S&P500 futures market. Our four main findings are as follows. First, the S&P500 futures predict the Chinese stock returns in the early (1-minute and 5-minute) and late (90-minute and 120-minute) phases of trading with predictability being the strongest at the 5-minute interval. Second, portfolio weight in favour of the Chinese stock market is maximised at the 5-minute trading, confirming the link between return predictability and portfolio optimisation. Third, when return predictability is strongest, hedgers need to take a significant short position in the futures market to minimise risk. Fourth, investor utility gains are associated with return predictability.

Our overall impression is that trading frequency during the day matters not only for predictability of Chinese stock returns but also for portfolio optimisation and hedging positions. Therefore, in analysing return predictability, portfolio optimisation, and hedging with intraday data it should not be assumed that investors are homogenous in trading within the day. We show that investor behaviour on a broad range of decisions varies from 1-minute trading to 120-minute trading. Therefore, ignoring this fact can be costly in terms of understanding the behaviour of investors.

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