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How Predictable is the Chinese Stock Market?

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HOW PREDICTABLE IS THE CHINESE STOCK MARKET?

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How Predictable Is The Chinese Stock Market?

by

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Abstract

We analyze return predictability for the Chinese stock market, including the aggregate market portfolio and the components of the aggregate market, such as portfolios sorted on industry, size, book-to-market and ownership concentration. Considering a variety of economic variables as predictors, both in-sample and out-of-sample tests highlight significant predictability in the aggregate market portfolio of the Chinese stock market and substantial differences in return predictability across components. Among industry portfolios, Finance and insurance, Real estate, and Service exhibit the most predictability, while portfolios of small-cap and low ownership concentration firms also display considerable predictability. Two key findings provide economic explanations for component predictability: (i) based on a novel out-of-sample decomposition, time-varying macroeconomic risk premiums captured by the conditional CAPM model largely account for component predictability; (ii) industry concentration and market capitalization significantly explain differences in return predictability across industries, consistent with the information-flow frictions emphasized by Hong, Torous, and Valkanov (2007).

JEL classifications: C22, C53, G11, G12, G17

Keywords: Return predictability; Industries; Size; Book-to-market; Rational asset pricing; Information-flow frictions;

Contents

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Chapter 1

Introduction

Stock return predictability is crucial to many fundamental issues in finance, including portfolio allocation, the cost of capital, and market efficiency (Cochrane (2008)). It is thus not surprising that a voluminous literature exists on the predictability of stock returns, with numerous economic variables proposed as predictors.[1] Many studies report in-sample evidence of return predictability, and despite some thorny econometric issues, the emerging consensus from in-sample studies is that stock returns contain a significant predictable component (Campbell (2000)). Out-of-sample evidence of return predictability, however, has proved more elusive, as exemplified by the recent study of Welch and Goyal (2008), who find that many popular predictors are unable to deliver consistent out-of-sample gains with respect to U.S. equity premium prediction relative to a simple forecast based on the historical average; also see Bossaerts and Hillion (1999) and Goyal and Welch (2003). Spiegel (2008) provides an overview of several recent major studies, including Campbell and Thompson (2008), who find greater out-of-sample predictability after imposing theoretically motivated restrictions. Furthermore, Rapach, Strauss, and Zhou (2009) and Kong, Rapach, Strauss, Tu and Zhou (2009) demonstrate that a forecast combination approach generates consistent and significant out-of-sample gains, and they link out-of-sample predictability to the real economy.

In contrast to the extant literature on return predictability, which focuses almost exclusively on the US data, the present paper examines return predictability for the *Chinese* stock market.[2] Investigating return predictability for the

[1]Predictors from the literature include the dividend-price ratio (Dow (1920), Fama and French (1988, 1989)), earnings-price ratio (Campbell and Shiller (1988, 1998)), book-to-market ratio (Kothari and Shanken (1997), Pontiff and Schall (1998)), nominal interest rates (Fama and Schwert (1977), Campbell (1987), Breen, Glosten, and Jagannathan (1989), Ang and Bekaert (2007)), inflation rate (Nelson (1976), Fama and Schwert (1977), Campbell and Vuolteenaho (2004)), term and default spreads (Campbell (1987), Fama and French (1989)), corporate issuing activity (Baker and Wurgler (2000), Boudoukh, Michaely, Richardson, and Roberts (2007)), consumption-wealth ratio (Lettau and Ludvigson (2001)), and stock market volatility (Guo (2006), Ludvigson and Ng (2007)). See Campbell (2000) and Welch and Goyal (2008) for surveys of the vast literature on return predictability.

[2]Lee and Rui (2000)documented some evidence of predictability of China's stock markets based on data ends in 1997 for only the market index

Chinese stock market is relevant for a number of reasons. First, analyzing the predictability of the Chinese stock market has potentially important implications for asset-pricing tests of the cross returns for the China stock market, as shown by Ferson and Harvey (1999) for the US data, among others, as well as measuring the cost of capital, along the lines of Fama and French (1997). (1997). Second, and in a related vein, analyzing Chinese stock return predictability helps to establish the proper benchmarks for many mutual funds that specialize in the China stock market. Third, an investigation of the Chinese stock market predictability improves our understanding of the return predictability worldwide besides the US.

Relative to the studies for US data, we do the following analyses on the Chinese stock market return predictability. First, we analyze predictability for the aggregate Chinese stock market and a large number of component portfolios – 13 industry, 10 size, 10 book-to-market and 10 ownership concentration portfolios –and potential predictors—9 economic variables following Welch and Goyal (2008). Second, we employ both in-sample and out-of-sample tests of component predictability, and our out-of-sample tests focus on the ability of a *forecast combination* method to outperform historical average benchmark forecasts. As recently shown by Rapach, Strauss, and Zhou (2009) and Kong, Rapach, Strauss, Tu and Zhou (2009) in the context of the US stock market predictability, the forecast combination approach incorporates information from many potential predictors in a tractable way to generate forecasts that are consistently superior to forecasts based on individual predictors.[3] As we demonstrate below, this is also the case for forecasting the Chinese stock returns. Third, as already mentioned, we extensively explore economic explanations for differences in return predictability across component portfolios such as the information-flow frictions recently emphasized by HTV.

Our analysis on the Chinese stock market return predictability uncovers a number of interesting and distinct empirical facts. In-sample results reveal that economic variables, such as dividend yield and turnover, significantly predict one-month-ahead returns for the aggregate market portfolio and most portfolios sorted by industry, size, book-to-market or ownership concentration; other economic variables, such as the dividend price ratio significantly predict some industries but not others. In addition, using the economic variables as predictors yields differences in predictability across components. For example, predictive regression models for Manufacturing, Finance and insurance, Real estate, and Service have economically sizable average R^2 statistics above 2%, while these same predictors have much smaller explanatory power in predictive regression models for Mining, Information technology and Communication and cultural industry, where the average R^2 statistics are less or close to 1%. There exist differences in in-sample

portfolios.

[3]While forecast combination has received considerable recent attention in the macroeconomic forecasting literature (see, e.g., Stock and Watson (1999, 2003, 2004)), applications in the finance literature are relatively rare. In addition to Rapach, Strauss, and Zhou (2009), Aiolfi and Favero (2005), Timmermann (2008), and Huang and Lee (2009) apply different types of combining methods to forecast aggregate market returns. Also see Mamaysky, Spiegel, and Zhang (2007), who find that combining predictions from an ordinary least squares model and the Kalman filter model of Mamaysky, Spiegel, and Zhang (2008) significantly increases the number of mutual funds with predictable out-of-sample alphas.

predictability across size, book-to-market and ownership concentration sorted portfolios as well.

Our out-of-sample test results using forecast combination reveal extensive predictability in real time for the aggregate market portfolio and a number of component portfolios. For the forecast evaluation period of January 2002 to June 2009, we find significant out-of-sample return predictability for all the 13 industry portfolios. Furthermore, the degree of out-of-sample predictability is substantially greater for certain industries, according to the Campbell and Thompson (2008) out-of-sample R^2 statistic. The economic variables significantly predict out-of-sample returns for all of the size, book-to-market and ownership concentration sorted portfolios. In addition, when excluding the bubble period of 2007 - 2008, using the subperiod from January 2002 to December 2006 as the forecast evaluation period, the degree of predictability increases substantially as size decreases, and the predictability of the smallest size portfolio is very strong. Similarly, there are differences in the degree of predictability across the book-to-market and ownership concentration sorted portfolios. Overall, our in-sample and out-of-sample predictive regression results demonstrate that the degree of predictability for the Chinese stock market is strong and can vary significantly across component portfolios.

We explore economic explanations for component predictability of Chinese stock market using two approaches. First, we implement a method of forming combination forecasts of component returns based on a conditional asset-pricing model. This allows us to decompose out-of-sample component predictability into exposure to time-varying macroeconomic risk premiums and alpha predictability. Considering conditional asset-pricing models based on the CAPM model, our results suggest that exposure to time-varying macroeconomic risk premiums accounts for most of the out-of-sample predictability in component portfolios, with greater exposure typically associated with enhanced predictability for size and ownership concentration sorted portfolios. Second, in the spirit of HTV, we examine the importance of information-flow frictions in explaining differences in return predictability across industry portfolios. We find that both industry concentration and industry capitalization are negatively and significantly related to the degree of return predictability across industries. HTV posit that information about macroeconomic fundamentals is less readily known in some industries and thus diffuses more slowly across the broader equity market, and our findings support HTV's emphasis on information-flow frictions. Overall, our results identify the components of the aggregate market that are subject to the greatest time-varying macroeconomic risk exposure and information-flow frictions, and they suggest that these factors are important in understanding return predictability for Chinese stock market.

The remainder of the paper is organized as follows. Section I provides statistical evidence on the predictability of the Chinese stock portfolio returns based on in-sample tests. Section II analyzes return predictability using out-of-sample tests. Section III considers economic reasons for return predictability. Section IV concludes.

Chapter 2

In-Sample Predictability Tests

This section outlines the predictive regression model framework, describes the data, and reports in-sample test results of predictability for the Chinese stock returns.

2.1 Econometric Methodology

Following much of the literature, we analyze stock return predictability in the context of a bivariate predictive regression model:

$$r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}, \tag{2.1}$$

where $r_{i,t}$ is the return on portfolio i in excess of the risk-free interest rate, $x_{j,t}$ is a potential predictor variable, and $e_{i,t}$ is a zero-mean disturbance term. In contrast to the vast literature on return predictability for the US data, in which $r_{i,t}$ is the excess return on a US stock return, we are interested in return predictability when $r_{i,t}$ is a return of a Chinese stock. More specifically, we analyze return predictability for the aggregate market portfolio and its components including 13 industry, 10 size, 10 book-to-market and 10 ownership concentration sorted portfolios for the Chinese stock market. (The data are described in detail below.)

The predictive ability of $x_{j,t}$ with respect to $r_{i,t}$ is typically analyzed by inspecting the t-statistic corresponding to $\hat{b}_{i,j}$, the ordinary least squares (OLS) estimate of $b_{i,j}$ in (2.1). Under the null hypothesis of no predictability, $b_{i,j} = 0$; the constant expected excess return model prevails ($r_{i,t} = a_i + \varepsilon_{i,t}$). Under the alternative hypothesis, $b_{i,j}$ is different from zero, and $x_{j,t}$ contains information useful for predicting $r_{i,t}$; a time-varying expected excess return model applies. There is a well-known small-sample bias associated with estimating (2.1) arising from the fact that $x_{j,t}$ is not an exogenous regressor (Stambaugh (1986, 1999)). This potentially complicates inference using conventional asymptotics. We thus base our inference on a bootstrap procedure similar to the procedures used by, for example, Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997), Kilian (1999), and Rapach and Wohar (2006).[1] Studies of predictability sometimes consider long-horizon regressions, but this raises additional econometric issues due to overlapping return observations; see, for example, Richardson and Stock (1989), Valkanov (2003), and Boudoukh, Richardson, and Whitelaw (2008). To avoid these issues, and for brevity, we focus on single-period (monthly) returns in our applications. We also use one-sided tests of statistical significance, since this provides more powerful tests, and theory typically suggests the expected sign of $b_{i,j}$ (Inoue and Kilian (2004)).

2.2 Data

We analyze return predictability for the aggregate market portfolio and its components including 13 industry, 10 size, 10 book-to-market and 10 ownership concentration sorted portfolios for the Chinese stock market. All the return data come from RESSET including all normal (without Special Treatment symbol issued by CSRC) China A-share stocks listed in Shanghai and Shenzhen stock exchanges. First, for the aggregate market return, we use the value-weighted return from 1996:07 to 2009:06 from RESSET including all normal (without Special Treatment symbol issued by CSRC) China A-share stocks listed in Shanghai and Shenzhen stock exchanges. The risk-free return is also obtained from RESSET to construct the excess stock return. Second, for the industry return, following the industry classification by China Securities Regulatory Commission (CSRC), we use monthly returns on 13 industry portfolios available from 1996:07 to 2009:06 from RESSET: AGRIC (Agriculture, Forestry, and Fishing), MINES (Mining), MANUF (Manufacturing Industries), UTILS (Electric, Gas, Water production and Supply), CNSTR (Construction),TRANS (Transportation and storage),INFTK (Information technology), WHTSL (wholesale and Retail store), MONEY(Finance and insurance), PROPT (Real estate), SRVC (Service industry), MEDIA (Communication and cultural industry), MULTP (conglomerate and other industry). The industry portfolios are constructed at the end of each June using the June industry classification. The portfolios for July of year t to June of t+1 include all normal A-share stocks listed in Shanghai and Shenzhen stock exchanges for which we have industry classification data for June of t. Third, the monthly returns of the 10 portfolios sorted on market capitalization, in ascending order denoted by S1, ..., S10, are constructed at the end of each June using the June market equity with equal number of firms in each portfolio. The portfolios for July of year t to June of year t+1 include all normal A-share stocks listed in Shanghai and Shenzhen stock exchanges

[1] The bootstrap is designed to avoid finite-sample size distortions. There are estimation procedures based on alternative asymptotic frameworks that provide potentially more powerful tests of return predictability while controlling for size distortions; see, for example, Campbell and Yogo (2006). Nevertheless, basing inference on OLS estimation of (2.1) and the bootstrap procedure provides extensive evidence of predictability for a number of component portfolio returns, so low power does not seem to be a serious problem for our applications. Bayesian methods have also been developed for predictive regression models like (2.1) (see, e.g., Stambaugh (1999)) and for predictive systems (Pástor and Stambaugh (2008)). While beyond the scope of the present paper, it would be interesting in future research to examine predictability for the component portfolios we consider using Bayesian methods.

for which we have market equity data for June of year t. Fourth, the monthly returns for the 10 portfolios sorted on book-to-market value, in ascending order denoted by BM1, ..., BM10, are formed on BE/ME at the end of each June with equal number of firms in each portfolio. The BE used in June of year t is the book equity for the last fiscal year end in t-1. ME is price times shares outstanding for the June of year t. The portfolios for July of year t to June of t+1 include all normal A-share stocks listed in Shanghai and Shenzhen stock exchanges for which we have ME for June of t, and BE for t-1. Finally, the monthly returns for the 10 portfolios sorted on ownership concentration percentage, in ascending order denoted by OC1, ..., OC10, are formed on ownership concentration percentage at the end of each June with equal number of firms in each portfolio. The ownership concentration percentage used in June of year t is the largest shareholder share holding percentage for the last fiscal year end in t-1. The portfolios for July of year t to June of t+1 include all normal A-share stocks listed in Shanghai and Shenzhen stock exchanges for which we have ME for June of t, and largest shareholder share holding percentage for t-1.

As potential predictors of component returns, we consider a group of 9 economic variables for China market:[2]

- Dividend-payout ratio (log), D/E: difference between the log of dividends and log of earnings for A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends and earnings are measured using a one-year moving sum .And they are from RESSET.

- Stock variance, SVAR: sum of squared daily returns on the Value-weighted A-share market return.

- Inflation, INF: calculated from the CPI from the Bureau of Statistics; following Welch and Goyal (2008), since inflation rate data are released in the following month, we use $x_{i,t-2}$ in (2.1) for inflation.

- Dividend-price ratio (log), D/P: difference between the log of dividends and log of prices for all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends are measured using a one-year moving sum.

- Dividend yield (log), D/Y: difference between the log of dividends and log of lagged prices, where dividends are measured using a one-year moving sum.

- Earnings-price ratio (log), E/P: difference between the log of earnings and log of prices on all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where earnings are measured using a one-year moving sum.

- Book-to-market ratio, B/M: ratio of book value to market value for A-share stocks listed in Shanghai and Shenzhen stock exchanges. Book values from the annul reports and interim reports are from RESSET. For the months of January to March, this is computed by dividing book value of June of previous year by the price at the end of the current month. For the months of April to September, this is computed by dividing book value at the end

[2]The 9 economic variables used here is a subset of the 14 economic variables of Welch and Goyal (2008) by excluding 5 economic variables that we do not have the data for the China market.

of previous year by the price at the end of the current month. For the months of October to December, this is computed by dividing book value of June of current year by the price at the end of the current month.

- Net equity expansion, NTIS: ratio of twelve-month moving sums of new equity issues to market capitalization at the end of the current month by A-share stocks listed in Shanghai and Shenzhen stock exchanges. New equity issues are from China Securities Regulatory Commission (CSRC).

- Turnover, TO: ratio of trading value to market capitalization for A-share stocks listed in Shanghai and Shenzhen stock exchanges. Both trading value and market capitalization are obtained from CEIC.

Table I reports summary statistics for excess returns for the aggregate market portfolio and its component portfolios: industry, size, book-to-market and ownership concentration portfolios, as well as the 9 economic variables, for 1996:07 – 2009:06. Panel B shows that average monthly industry returns range from 0.65% (CNSTR) to 2.33% (MINES), while the standard deviations range from 9.25% (UTILS) to 12.11% (MEDIA). As is well known, Panels C and D show that returns are generally higher and more volatile for small-cap or higher book-to-market firms.

[Insert Table I about here]

2.3 The Aggregate Market Portfolio Excess Returns

The MKT row of Table II reports estimation results for (2.1) when $r_{i,t}$ is the excess return for the aggregate market portfolio and $x_{j,t}$ is one of the 9 economic variables. After accounting for the lagged predictor in (2.1), our estimation sample is 1996:07–2009:06. The entries in the table report the t-statistic corresponding to $b_{i,j}$ in (2.1) (top number) and R^2 statistic (bottom number) for each industry/predictor combination. Average R^2 statistics across predictors are shown in the last column of Table II. While predictive regression models can have relatively small R^2 statistics, Campbell and Thompson (2008) show that an R^2 greater than approximately 0.5% for monthly returns can signal economically meaningful predictability gains; also see Kandel and Stambaugh (1996) and Xu (2004). Three predictors— D/Y, INF, and TO —enter significantly in (2.1) for the excess return on the aggregate market portfolio. As shown in the penultimate row of Table II, these are also the predictors that most frequently predict excess returns across industries.

2.4 Industry Portfolio Excess Returns

The penultimate row of Table II reports estimation results for (2.1) when $r_{i,t}$ is the excess return for an industry portfolio and $x_{j,t}$ is one of the 9 economic variables. Average R^2 statistics across predictors (industries) are shown in the last column (rows) of Table II. The number of industries for which a given predictor is significant in (2.1) at the 5% level is also shown.

[Insert Table II about here]

Among the 13 industry returns considered, D/Y, INF, and TO are significant predictors of excess returns for 7, 5, and 11 industry portfolios, respectively. From this perspective, there is—not surprisingly—a link between aggregate market predictability and predictability across industries. Nevertheless, there are important differences in predictability across industry portfolios. Looking at the last column of Table II, industry returns appear most predictable on average for MANUF, MONEY, PROPT, and SRVC, where the average R^2 across predictors is greater than or equal to 2.0%. Predictability is weaker on average in industries such as MINES, INFTK and MEDIA, where the average R^2 statistics are less or close to 1%.

2.5 Size Portfolio Returns

We next examine return predictability for 10 portfolios sorted on market capitalization, and the results are reported in Table III. Relative to the industry portfolios analyzed in the previous subsection, there appears to be more uniformity in the degree of return predictability across size portfolios. The two economic variables—D/Y and TO—that are significant predictors of aggregate market returns are also significant predictors of returns for 6–10 of the size portfolios, and the average R^2 statistics are relatively stable across the size portfolios.

[Insert Table III about here]

2.6 Book-to-Market Portfolio Returns

Table IV reports results for predictive regression models of book-to-market portfolios with the 9 economic variables serving as predictors. The results are broadly similar to those in Table III for the size portfolios in that pronounced differences in predictability across component portfolios are not clearly evident. For example, the average R^2 statistics in the last column of Table IV are similar across the book-to-market portfolios.

[Insert Table IV about here]

2.7 Ownership-concentration Portfolio Returns

Table V reports results for predictive regression models of ownership concentration portfolios with the 9 economic variables serving as predictors. The results are broadly similar to those in Table IV for the size portfolios in that pronounced differences in predictability across component portfolios are not clearly evident. For example, the average R^2 statistics in the last column of Table V are similar across the book-to-market portfolios. Although the differences in the in-sample predictability across component portfolios are not clearly evident for the size, book-to-market and ownership concentration portfolios, the differences in the out-of-sample predictability across component portfolios are significant for all of the three sets of portfolios as shown below.

[Insert Table V about here]

Chapter 3

Out-of-Sample Predictability Tests

As indicated in the introduction, out-of-sample return predictability has been more difficult to establish, especially on a consistent basis over time. We next consider out-of-sample tests of return predictability for Chinese stock returns. This section describes the construction of the out-of-sample forecasts, forecast evaluation methods, and out-of-same test results.

3.1 Econometric Methodology

Following Campbell and Thompson (2008) and Welch and Goyal (2008), we generate out-of-sample forecasts of excess returns using an expanding estimation window. More specifically, we first divide the total sample of T observations for $r_{i,t}$ and $x_{j,t}$ into an in-sample portion composed of the first n_1 observations and an out-of-sample portion composed of the last n_2 observations. The initial out-of-sample forecast of the excess return on a component portfolio based on the predictor $x_{j,t}$ is given by

$$\hat{r}_{i,n_1+1} = \hat{a}_{i,n_1} + \hat{b}_{i,j,n_1} x_{j,n_1}, \tag{3.1}$$

where $\hat{a}_{i,n_1}$ and $\hat{b}_{i,j,n_1}$ are the OLS estimates of a_i and $b_{i,j}$, respectively, in (2.1) generated by regressing $\{r_{i,t}\}_{t=2}^{n_1}$ on a constant and $\{x_{j,t}\}_{t=1}^{n_1-1}$. The next out-of-sample forecast is given by

$$\hat{r}_{i,n_1+2} = \hat{a}_{i,n_1+1} + \hat{b}_{i,j,n_1+1} x_{j,n_1+1}, \tag{3.2}$$

where $\hat{a}_{i,n_1+1}$ and $\hat{b}_{i,j,n_1+1}$ are generated by regressing $\{r_{i,t}\}_{t=2}^{n_1+1}$ on a constant and $\{x_{j,t}\}_{t=1}^{n_1}$. Proceeding in this manner through the end of the out-of-sample period, we generate a series of n_2 out-of-sample excess return forecasts based on $x_{j,t}$ ($\{\hat{r}_{i,t+1}\}_{t=n_1}^{T-1}$). We emphasize that this out-of-sample forecasting exercise mimics the situation of a forecaster in real time. As in our in-sample tests in Section I above, a constant expected excess return model is the relevant benchmark model under the null hypothesis of no predictability. Following Campbell and Thompson (2008) and Welch and Goyal (2008), we simulate real-time forecasts based on the constant expected excess return model using the historical average, $\bar{r}_{i,t+1} = \sum_{j=1}^{t} r_{i,j}$.

We use the Campbell and Thompson (2008) out-of-sample R^2 statistic, R^2_{OS}, to compare the $\hat{r}_{i,t+1}$ and $\bar{r}_{i,t+1}$ forecasts. The R^2_{OS} statistic is akin to the familiar in-sample R^2 and is given by

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}. \tag{3.3}$$

The R^2_{OS} statistic measures the reduction in mean square prediction error (MSPE) for the predictive regression model forecast compared to the historical average forecast. Thus, when $R^2_{OS} > 0$, the $\hat{r}_{i,t}$ forecast outperforms the $\bar{r}_{i,t}$ forecast according to the MSPE metric. We also test whether the predictive regression model forecast has a significantly lower MSPE than the historical average benchmark forecast, which is tantamount to testing the null hypothesis that $R^2_{OS} \leq 0$ against the alternative hypothesis that $R^2_{OS} > 0$. The most popular test procedure is the Diebold and Mariano (1995) and West (1996) statistic, which has an asymptotic standard normal distribution when comparing forecasts from non-nested models. Clark and McCracken (2001) and McCracken (2007), however, show that this statistic has a non-standard distribution when comparing forecasts from *nested* models, as is clearly the case when comparing the predictive regression model forecast to the historical average forecast.

Clark and West (2007) develop an adjusted version of the Diebold and Mariano (1995) and West (1996) statistic that can be used in conjunction with the standard normal distribution to generate asymptotically valid inferences when comparing forecasts from nested linear models. The Clark and West (2007) *MSPE-adjusted* statistic is conveniently calculated by first defining

$$f_{i,t+1} = (r_{i,t+1} - \bar{r}_{i,t+1})^2 - [(r_{i,t+1} - \hat{r}_{i,t+1})^2 - (\bar{r}_{i,t+1} - \hat{r}_{i,t+1})^2], \tag{3.4}$$

then regressing $\{f_{i,s+1}\}_{s=n_1}^{T-1}$ on a constant, and finally calculating the t-statistic corresponding to the constant. A p-value for a one-sided (upper-tail) test is then computed using the standard normal distribution. In Monte Carlo simulations, Clark and West (2007) demonstrate that the *MSPE-adjusted* statistic performs reasonably well in terms of size and power when comparing forecasts from nested linear models for a variety of sample sizes.

When estimating forecasting models, we use the first subperiod (1996.07 – 2001:12) of data as an in-sample period and compute excess return forecasts via an expanding estimation window, as described above. This leaves us with an out-of-sample forecast evaluation period of 2002:01–2009:6. This period covers the bubble period of the 2007-2008.

In addition to individual predictive regression model forecasts, we compute *combination forecasts* of component portfolio returns. We do this for two reasons. First, combination forecasts provide a convenient means for summarizing the collective predictive ability of a large number of individual predictors. Second, Rapach, Strauss, and Zhou (2009) recently find that combination forecasts substantially improve forecasts of aggregate market excess returns. More specifically, they show that combinations of forecasts generated by individual predictive regression models based on the economic variables from Welch and Goyal (2008) provide statistically and economically significant out-of-sample gains relative to the historical average forecast, despite the inconsistent and often poor out-of-sample performance of individual model forecasts. These gains likely stem from the ability of forecast combination to improve forecasting performance in the presence of substantial model uncertainty and instability.[1] An alternative approach to incorporating information from a large number of potential predictors is to include all of the potential predictors in a single multiple regression model, what Welch and Goyal (2008) call the "kitchen sink" model. Welch and Goyal (2008) and Rapach, Strauss, and Zhou (2009), however, show that the kitchen sink model performs very poorly in out-of-sample forecasting.[2]

We employ a simple forecast combining method: the mean of the individual predictive regression model forecasts. Rapach, Strauss, and Zhou (2009) find that the mean combination forecast performs well with respect to forecasting aggregate market excess returns. The mean combination forecast has also proved useful in macroeconomic contexts; see, for example, Stock and Watson (2003) with respect to forecasting output growth and inflation.

3.2 The Aggregate Market Portfolio Excess Returns

The MKT row of Table VI reports out-of-sample results for excess returns on aggregate market portfolios using the 9 economic variables as predictors. The entries in Table VI give the R^2_{OS} statistic (in percent). Among the 9 economic variables, only TO produces a significant R^2_{OS} (7.79%) for the excess return on the aggregate market portfolio. The combination forecast in the last column of Table VI yields a statistically significant and economically sizable R^2_{OS} of 3.13% for the aggregate market return.

3.3 Industry Portfolio Excess Returns

Turning to the industry portfolios, as shown by Table VI, we see some marked differences in predictability across industries. Focusing on the combination forecast results in the last column, TRANS, INFTK, MONEY, PROPT, and SRVC have R^2_{OS} statistics greater than 3.13%, and all are statistically significant. There are some individual

[1] See, for example, Hendry and Clements (2004) and Timmermann (2006).

[2] Rapach, Strauss, and Zhou (2009) analyze the restrictions implied by forecast combination relative to the unrestricted kitchen sink model. They argue that these restrictions improve forecasting performance in environments with a highly complex and constantly evolving data-generating process; also see the comparison of combination and kitchen sink model forecasts in Huang and Lee (2009). Another approach for incorporating information from a very large number of economic variables is factor analysis. Ludvigson and Ng (2007) apply this approach using 350 macroeconomic and financial variables in analyzing aggregate market return predictability.

predictors, especially TO, that produce relatively high R^2_{OS} statistics for most of the industries; for example, TO has an R^2_{OS} of 9.44% for PROPT and 8.95% for TRANS. Nevertheless, the combination forecasts can improve out-of-sample forecasting performance relative to most of the individual predictive regression models for some predictable industries, such as CNSTR and MEDIA.

[Insert Table VI about here]

While most of the industries evince significant return predictability, a few others, such as AGRIC, MINES, MANUF, UTILS, CNSTR, WHTSL, MEDIA, and MULTP, generally display substantially less return predictability. For these industries, the combination forecast R^2_{OS} statistics range from only 1.39%–3.03%, below 3.13%, the combination forecast R^2_{OS} statistics of the aggregate market portfolio. Overall, the out-of-sample results for industry portfolio returns reported in this section match up reasonably well with the in-sample results in Section I above.

[Insert Table VII about here]

3.4 Size Portfolio Returns

Table VII reports out-of-sample results for size portfolio excess returns using the 9 economic variables as predictors. Among the individual economic variables, relatively few have positive R^2_{OS} statistics. Again TO perform the best overall, with all positive and significant R^2_{OS} statistics. The R^2_{OS} statistics in the last column of Table VII show that the combination forecasts offer out-of-sample gains relative to the historical average forecasts for all of the size portfolios. These statistics are all positive and significant. Pronounced differences in predictability across size portfolios are evident: The R^2_{OS} statistics for the combination forecasts in Table VII vary between the range of 2.86%–5.75%. Although there is no clear pattern for the differences in predictability across size portfolios, as shown in Panel C of Table X, there is a downward trend in general from small to large size portfolios when using the subperiod of 2002:01 to 2006:12 as the the forecast evaluation period by excluding the bubble period of 2007 to 2009. Focusing on the results for the combination forecasts in the last column of the table, we see that the extent of predictability is strongest for S1, where the R^2_{OS} is an economically substantial 8.91%, while the R^2_{OS} falls to 3.08% for S10. In fact, the R^2_{OS} statistics decrease almost monotonically as size increases. The out-of-sample results presented in this section for size portfolios reinforce the in-sample results in Section I above.

[Insert Table VIII about here]

3.5 Book-to-Market Portfolio Returns

Out-of-sample results for book-to-market portfolio excess returns using 9 economic variables as predictors are reported in Table VIII. Similar to the results in Table VII for the size portfolios, TO perform the best overall, with all positive and significant R^2_{OS} statistics. The R^2_{OS} statistics in the last column of Table VIII show that the combination forecasts offer out-of-sample gains relative to the historical average forecasts for all of the book-to-market portfolios. These statistics are all positive and significant. Pronounced differences in predictability across book-to-market portfolios are evident: The R^2_{OS} statistics for the combination forecasts in Table VIII vary between the range of 2.38%–4.14%. Although similar to the size portfolios, there is again no clear pattern for the differences in predictability across book-to-market portfolios, as shown in Panel D of Table X, there is a downward trend in general from low to high book-to-market portfolios when using the subperiod of 2002:01 to 2006:12 as the the forecast evaluation period by excluding the bubble period of 2007 to 2009.

[Insert Table IX about here]

3.6 Ownership Concentration Portfolio Returns

Out-of-sample results for the ownership concentration portfolio excess returns using 9 economic variables as predictors are reported in Table IX. Similar to the results in Tables VII and VIII for the size and book-to-market portfolios, TO perform the best overall, with all positive and significant R^2_{OS} statistics. The R^2_{OS} statistics in the last column of Table VIII show that the combination forecasts offer out-of-sample gains relative to the historical average forecasts for all of the ownership concentration portfolios. These statistics are all positive and significant. Pronounced differences in predictability across book-to-market portfolios are evident: The R^2_{OS} statistics for the combination forecasts in Table IX vary between the range of 2.23%–6.24%. Although similar to the size and book-to-market portfolios, there is again no clear pattern for the differences in predictability across book-to-market portfolios, the R^2_{OS} statistics of the combination forecasts for the five portfolios with lower ownership concentration, OC1 to OC5, are generally larger than those R^2_{OS} statistics for the five portfolios with higher ownership concentration, OC6 to OC10. This is true, as shown in Panel E of Table X, when using the subperiod of 2002:01 to 2006:12 as the the forecast evaluation period by excluding the bubble period of 2007 to 2009.

[Insert Table X about here]

Chapter 4

Economic Explanations for Component Predictability

We next explore economic explanations for component predictability of the Chinese stock market, focusing on out-of-sample combination forecasts. This section presents results for two approaches based on rational/alpha predictability decompositions, and industry characteristics.

4.1 Decomposing Out-of-Sample Predictability

Studies such as Stambaugh (1983), Campbell (1987), Connor and Korajczyk (1989), Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), Kirby (1998), and Avramov (2004) analyze the implications of rational asset pricing for return predictability. This provides a framework for determining the extent to which component predictability results from exposure to time-varying systematic/macroeconomic risk premiums as opposed to alpha predictability, where the latter can be interpreted as corresponding to asset mispricing. We investigate this issue following Kong, Rapach, Strauss, TU ans zhou's (2009) out-of-sample approach based on combination forecasts of aggregate market and component portfolio returns.

Following Avramov (2004), among others, consider the following model for component i's excess return:

$$r_{i,t} = \alpha_i(x_{t-1}) + \beta_i' f_t + \varepsilon_{i,t}, \tag{4.1}$$

where x_{t-1} is an M-vector of lagged state variables or predictors, f_t is a K-vector of portfolio-based factors capturing systematic risk, and β_i is a K-vector comprised of component i's beta. Assume that

$$f_t = \lambda(x_{t-1}) + u_t, \tag{4.2}$$

where u_t is a zero-mean vector of disturbance terms. Equation (4.2) allows the factors to vary with the lagged state variables, leading to time-varying risk premiums. A conditional version of a rational asset-pricing model implies[1]

$$E(r_{i,t}|x_{t-1}) = \beta_i' E(f_t|x_{t-1}) = \beta_i' \lambda(x_{t-1}). \tag{4.3}$$

When $K = 1$, we can consider (4.3) as the conditional CAPM, so that f_t is a scalar representing the excess return on the aggregate market portfolio, and $\lambda(x_{t-1})$ is the expected market equity premium. Under rational asset pricing in the form of the conditional CAPM, any predictability in $r_{i,t}$ emanates solely from the predictability of aggregate market returns in conjunction with the sensitivity of $r_{i,t}$ to the market portfolio, as given by $\beta_i \lambda(x_{t-1})$, implying $\alpha_i(x_{t-1}) = 0 \, \forall \, t$. Predictability in $r_{i,t}$ beyond what is produced by $\beta_i \lambda(x_{t-1})$ represents alpha predictability, as it implies $\alpha_i(x_{t-1}) \neq 0 \, \forall \, t$. Insofar as (4.2) adequately captures systematic risk, $\alpha_i(x_{t-1}) \neq 0 \, \forall \, t$ corresponds to mispricing in component i.

We calculate *rational pricing-restricted* combination forecasts of $r_{i,t}$ based on (4.3) to decompose the R^2_{OS} statistics (in Section II) into their rational and alpha predictability portions. To begin, consider forming a combination forecast of $r_{i,t}$ based on (4.3) under the conditional CAPM. From Section II, we already have a time-t combination forecast of the aggregate market return that incorporates time-$(t-1)$ information from 9 economic variables; denote this forecast as $\hat{f}_t^C$, which can be viewed as a real-time estimate of $\lambda(t-1)$. It is straightforward to compute an estimate of β_i for time t by regressing the component i excess return on the aggregate market excess return using data from the beginning of the sample through $t-1$; denote this estimate by $\hat{\beta}_{i,t}$.[2] The rational pricing-restricted combination forecast of $r_{i,t}$ based on (4.3) is then given by

$$\hat{r}_{i,t}^R = \hat{\beta}_{i,t} \hat{f}_t^C. \tag{4.4}$$

In other words, one obtains this combination forecast with the use of an asset-pricing model, in this case, the conditional CAPM.

Denote the combination forecast of $r_{i,t}$ from Section II by $\hat{r}_{i,t}^C$. In contrast to $\hat{r}_{i,t}^R$, $\hat{r}_{i,t}^C$ does not impose the asset-pricing restriction given by (4.3). It thus constitutes an unrestricted combination forecast based on 9 economic variables that permits both rational and alpha predictability.

Then we are ready to decompose the R^2_{OS} statistic by computing two subsidiary R^2_{OS} statistics. The first is a modified version of (3.3) that measures the reduction in MSPE for the rational pricing-restricted combination forecast

[1]This specification assumes that β_i is time-invariant, following Stambaugh (1983), Campbell (1987), Connor and Korajczyk (1989), Kirby (1998), and Avramov (2004). Ferson and Harvey (1991), Evans (1994), and Ferson and Korajczyk (1995) present empirical evidence that time variation in risk premiums (λ) is substantially greater than that in β_i; also see Ghysels (1998). Note that our recursive out-of-sample estimation procedure for β_i, described below, allows for some time variation in β_i.

[2]Note that there is no "look-ahead" bias in doing this, as we only use data available at the time of forecast formation in estimating β_i.

relative to the historical average forecast,

$$R_{OS,R}^2 = 1 - \frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k}^R)^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}. \tag{4.5}$$

The $R_{OS,R}^2$ statistic gauges the extent of rational out-of-sample predictability in component i as implied by the conditional CAPM. The next statistic measures the decrease in MSFE for the unrestricted combination forecast compared to the rational pricing-restricted combination forecast,

$$R_{OS,\alpha}^2 = 1 - \frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k}^C)^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k}^R)^2}. \tag{4.6}$$

This statistic quantifies the degree of out-of-sample predictability beyond rational predictability, thereby providing a measure of out-of-sample alpha predictability. Observe from (3.3), (4.5), and (4.6) that

$$R_{OS,\alpha}^2 = 1 - \left[\frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k}^C)^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}\right]\left[\frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}_{i,n_1+k}^R)^2}\right] = 1 - \left(\frac{1 - R_{OS}^2}{1 - R_{OS,R}^2}\right). \tag{4.7}$$

Solving for R_{OS}^2 in (4.7), we have

$$R_{OS}^2 = R_{OS,R}^2 + R_{OS,\alpha}^2 - R_{OS,R}^2 R_{OS,\alpha}^2. \tag{4.8}$$

For "small" $R_{OS,R}^2$ and $R_{OS,\alpha}^2$, the cross-product term is approximately zero, so that

$$R_{OS}^2 \approx R_{OS,R}^2 + R_{OS,\alpha}^2. \tag{4.9}$$

Our approach thus (approximately) dichotomizes R_{OS}^2, a measure of total out-of-sample predictability, into $R_{OS,R}^2$ and $R_{OS,\alpha}^2$, the sum of predictability due to exposure to time-varying risk premiums and alpha variation, respectively.

Table XI reports $R_{OS,R}^2$ and $R_{OS,\alpha}^2$ statistics for combination forecasts that use 9 economic variables as predictors. Panel A of Table XI indicates that 12 of the 13 industries have positive and significant $R_{OS,R}^2$ statistics, meaning that rational pricing as captured by the conditional CAPM explains a significant portion of the out-of-sample predictability for almost all industries. Furthermore, $R_{OS,\alpha}^2$ is only significant for four industries (INFTK, MONEY, PROPRT, and SRVC), and the magnitude of the $R_{OS,\alpha}^2$ statistics can be substantially less than that of the corresponding $R_{OS,R}^2$ statistics. Taken together, these results suggest that the out-of-sample predictability in industry returns based on economic variables is largely attributable to rational out-of-sample predictability based on the conditional CAPM as opposed to alpha predictability. The results for the size and book-to-market portfolios in Panels B and C, respectively, of Table XI are similar to those in Panel A. Again, little of the out-of-sample predictability in size and book-to-market portfolios appears attributable to alpha predictability except for a few cases. As for the ownership concentration portfolios, Panel D shows that the out-of-sample predictability in the five portfolios with lower ownership concentration, OC1 to OC5, appears attributable to both rational factor predictability and alpha predictability.

[Insert Table XI about here]

Rational asset pricing built on the conditional CAPM suggests that the out-of-sample gains in predictability for the rational pricing-restricted forecast relative to the historical average forecast should be more pronounced for components with greater exposure to the market portfolio. We investigate the relationship between the extent of rational predictability and a component's beta in Figure 1. Each panel in Figure 1 presents a scatterplot relating a component's $R^2_{OS,R}$ statistic to the average $\hat{\beta}_{i,t}$ over the out-of-sample period. Each panel includes a fitted regression line and estimation results for a cross-section regression model with $R^2_{OS,R}$ (average $\hat{\beta}_{i,t}$) as the regressand (regressor).[3]

[Insert Figure 1 about here]

Panels B and D of Figure 1 show a clear positive correlation between the $R^2_{OS,R}$ statistics and average β_i estimates for the size and ownership concentration portfolios . Furthermore, the estimated slope coefficients reveal a significant relationship in each panel, and the R^2 statistics for the cross-section regressions are a reasonably sizable 14% and 27% in Panels B and D, respectively. In contrast to the results in Figure 1, Panels B and D, there is no evidence of a significantly positive relationship between $R^2_{OS,R}$ and the average β_i estimates for the industry portfolios and the book-to-market portfolios in Panels A and C.

While beyond the scope of the present paper, we could consider additional conditional asset-pricing models, including, for example, models with additional potential macroeconomic risk factors from Chen, Roll, and Ross (1986).[4] Nevertheless, it is interesting that conditional asset-pricing models based on the well-known CAPM model can account for most of the out-of-sample predictability in a variety of component portfolio returns.

4.2 Out-of-Sample Predictability and Industry Characteristics

To gain additional insight into economic explanations for differences in component predictability, we examine the relationships between the R^2_{OS} statistics for the combination forecasts in the last column of Table VI and two industry characteristics, industry concentration share and industry market capitalization share. This is motivated by the information-flow frictions recently emphasized by HTV. If information-flow frictions are pertinent, we expect stronger predictability in industries with greater concentration, since the equity market is better able to acquire information for the relatively small number of large firms in these industries. In contrast, information should be more costly to obtain—and information-flow frictions more relevant—for industries characterized by a comparatively large number of small firms; we thus expect a greater degree of predictability for these industries. In a similar vein, we posit a lesser (greater)

[3] An intercept term is included in the cross-section regression model. The t-statistics reported in Figure 1 are based on White (1980) heteroskedasticity-consistent standard errors.

[4] Ferson and Harvey (1991) and Ferson and Korajczyk (1995) consider these factors in conditional asset-pricing models. We leave the analysis of additional conditional asset-pricing models to future research.

degree of predictability for industries that make up a larger (smaller) share of the overall equity market.

Panel A (B) of Figure 2 presents a scatterplot relating the R^2_{OS} statistics for the combination forecasts based on lagged industry returns in Table VI to industry concentration (industry market capitalization). Industry concentration is measured as the sum of the earnings share (in percent) accruing to the eight largest firms in the industry, while industry market capitalization is measured as the industry market capitalization share of the entire equity market on average over our sample period.

[Insert Figure 2 about here]

Panel A of Figure 2 shows a negative correlation between industry concentration and out-of-sample predictability across industries. In addition, although a cross-section OLS regression of the R^2_{OS} statistics on industry concentration yields a negative but not significant slope coefficient (t-statistic equals -0.29) and a relatively small R^2 statistic of 0.77%, the t-statistic and the R^2 statistic become much larger after dropping the two industries (TRANS and INFTK). These results are in line with our conjecture that less concentrated industries are typically more predictable due to information-flow frictions. Panel B of Figure 2 shows a negative correlation between industry market capitalization and out-of-sample predictability, and the cross-section regression confirms a significant relationship (large t-statistic) with relatively high explanatory power (high R^2) after dropping the two industries (TRANS and INFTK). Taken together, the results in Figure 2 signals the relevance of market structure and size for the predictability of industry returns.

Chapter 5

Conclusion

We conduct an extensive analysis of return predictability in the Chinese stock market for the aggregate market portfolio and a variety of its component portfolios using a large number of potential predictors from the literature on stock return predictability. Focusing on the aggregate market portfolio and four sets of component portfolios sorted on industry, size, book-to-market and ownership concentration, in-sample and out-of-sample tests both point to significant predictability and important differences in predictability across component portfolios. More specifically, we find that returns are more predictable for particular industries, small-cap and low ownership concentration stocks. Employing a forecast combination approach, the predictability we find is robust to the use of individual predictors and particular sample periods.

We also explore economic explanations for the differences in return predictability across component portfolios of the Chinese aggregate market portfolio. We implement an innovative decomposition based on combination forecasts that apportions out-of-sample component predictability into exposure to time-varying macroeconomic risk premiums and alpha predictability. Our results suggest that exposure to time-varying risk premiums largely accounts for the out-of-sample predictability in component portfolios. Furthermore, differences in return predictability across industry portfolios are significantly related to industry concentration and capitalization, and the direction of the relationships are consistent with information-flow frictions in the equity market (Hong, Torous, and Valkanov (2007)). Overall, our results point to the importance of time-varying macroeconomics risk exposure and information-flow frictions in understanding return predictability more generally.

Our results could be extended in some directions. For instance, we focus on a large number of predictors from the literature on US stock return predictability. It would be interesting to also consider China-specific predictors such as bank loan expansion rate given that Chinese stock market is likely to subject to the liquidity in a larger degree than a developed market like US. We leave these extensions to future research.

References

Aiolfi, Marco, and Carlo A. Favero, 2005, Model uncertainty, thick modelling and the predictability of stock returns, *Journal of Forecasting* 24, 233–254.

Ang, Andrew, and Geert Bekaert, 2007, Return predictability: Is it there? *Review of Financial Studies* 20, 651–707.

Avramov, Doron, 2002, Stock return predictability and model uncertainty, *Journal of Financial Economics* 64, 423–458.

Avramov, Doron, 2004, Stock return predictability and asset pricing models, *Review of Financial Studies* 17, 699–738.

Avramov, Doron, and Tarun Chordia, 2006, Predicting stock returns, *Journal of Financial Economics* 82, 387–415.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219–2257.

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

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael R. Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance*, 62, 877–915.

Boudoukh, Jacob, Matthew Richardson, and Robert F. Whitelaw, 2008, The myth of long-horizon predictability, *Review of Economic Studies* 21, 1575–1605.

Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989, Economic significance of predictable variations in stock index returns, *Journal of Finance* 64, 1177–1189.

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

Campbell, John Y., 2000, Asset pricing at the millennium, *Journal of Finance* 55, 1515–1567.

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

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

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

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19–23.

Campbell, John Y., and Motohiro Yogo, 2006, Efficient tests of stock return predictability, *Journal of Financial Economics* 81, 27–60.

Chen, Nai-fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383–403.

Clark, Todd E., and Michael W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85–110.

Clark, Todd E., and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

Cochrane, John H., 2008, The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21, 1533–1575.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Connor, Gregory, and Robert A. Korajczyk, 1989, An intertemporal equilibrium asset pricing model, *Review of Financial Studies* 2, 373–392.

Cooper, Michael, Huseyin Gulen, and Maria Vassalou, 2002, Investing in size and book-to-market portfolios: Some new trading rules, manuscript, Purdue University.

Diebold, Francis X., and Robert S. Mariano, 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13, 253–263.

Dow, Charles H., 1920, Scientific stock speculation, *The Magazine of Wall Street*.

Evans, Martin D.D., 1994, Expected returns, time-varying risk, and risk premia, *Journal of Finance* 49, 655–679.

Eleswarapu, Venkat R., and Ashish Tiwari, 1996, Business cycles and stock market returns: Evidence using industry-based portfolios, *Journal of Financial Research* 19, 121–134.

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

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–155.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

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

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation in economic risk premiums, *Journal of Political Economy* 99, 385–415.

Ferson, Wayne E., and Campbell R. Harvey, 1999, Conditioning variables and the cross section of stock returns, *Journal of Finance* 54, 1325–1360.

Ferson, Wayne E., and Robert A. Korajczyk, 1995, Do arbitrage pricing models explain the predictability of stock returns, *Journal of Business* 68, 309–349.

Ghysels, Eric, 1998, On stable factor structures in the pricing of risk: Do time-varying betas help or hurt? *Journal of Finance* 53, 549–573.

Goyal, Amit, and Ivo Welch, 2003, Predicting the equity premium with dividend ratios, *Management Science* 49, 639–654.

Guo, Hui, 2006, On the out-of-sample predictability of stock market returns, *Journal of Business* 79, 645–670.

Hendry, David F., and Michael P. Clements, 2004, Pooling of forecasts, *Econometrics Journal* 7, 1–31.

Henkel, Sam J., J. Spencer Martin, and Frederico Nadari, 2008, Time-varying short-horizon predictability, manuscript, Carnegie Mellon University.

Hong, Harrison, Walter Torous, and Rossen Valkanov, 2007, Do industries lead stock markets? *Journal of Financial Economics* 83, 367–396.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, *Review of Financial Studies* 20, 1113–1138.

Huang, Huiyu, and Tae-Hwe Lee, 2009, To combine forecasts or to combine information, *Econometric Reviews*, forthcoming.

Inoue, Atsushi, and Lutz Kilian, 2004, In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews* 23, 371–402.

Kandel, Shmuel, and Robert F. Stambaugh, 1996, On the predictability of stock returns: An asset allocation perspective, *Journal of Finance* 51, 385–424.

Kilian, Lutz, 1999, Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? *Journal of Applied Econometrics* 14, 491–510.

Kirby, Chris, 1998, The restrictions on predictability implied by rational asset pricing models, *Review of Financial Studies* 11, 343–382.

Kothari, S.P., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169–203.

Lee,Cheng F.,and Oliver M. Rui,2000,Does trading volume contain information to predict stock returns? evidence from China's stock markets, *Review of Quantitative Finance and Accounting* 14,341–360.

Lettau, Martin, and Sydney C. Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815–849.

Liew, Jimmy, and Maria Vassalou, 2000, Can book-to-market, size and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57, 221–245.

Ludvigson, Sydney C., and Serena Ng, 2007, The empirical risk-return relation: A factor analysis approach, *Journal of Financial Economics* 83, 171–222.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2007, Improved forecasting of mutual fund alphas and betas, *Review of Finance* 11, 359–400.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2008, Estimating the dynamics of mutual fund alphas and betas, *Review of Financial Studies* 21, 233–264.

Mark, Nelson C., 1995, Exchange rates and fundamentals: Evidence on long-horizon predictability, *American Economic Review* 85, 201–218.

McCracken, Michael W., 2007, Asymptotics for out of sample tests of Granger causality, *Journal of Econometrics* 140, 719–752.

Menzly, Lior, and Oguzhan Ozbas, 2006, Cross-industry momentum, manuscript, University of Southern California.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum? *Journal of Finance* 54, 1249–1290.

Nelson, Charles R., 1976, Inflation and the rates of return on common stock, *Journal of Finance* 31, 471–483.

Nelson, Charles R., and Myung J. Kim, 1993, Predictable stock returns: The role of small sample bias, *Journal of Finance* 48, 641–661.

Pástor, Ľuboš, and Robert F. Stambaugh, 2008, Predictive systems: Living with imperfect predictors, *Journal of Finance*, forthcoming.

Perez-Quiros, Gabriel, and Allan Timmermann, 2000, Firm size and cyclical variations in stock returns, *Journal of Finance* 55, 1229–1262.

Pontiff, Jeffrey, and Lawrence D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141–160.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2009, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies*, forthcoming.

Kong Aiguo, David E. Rapach, Jack K. Strauss, Jun Tu, and Guofu Zhou, 2009, How pPredictable are components of the aggregate market portfolio? Working Paper

Rapach, David E., and Mark 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.

Richardson, Matthew, and James H. Stock, 1989, Drawing inferences from statistics based on multi-year asset returns, *Journal of Financial Economics* 25, 323–348.

Spiegel, Matthew, 2008, Forecasting the equity premium: Where we stand today, *Review of Financial Studies* 21, 1453–1454.

Stambaugh, Robert F., 1983, Arbitrage pricing with information, *Journal of Financial Economics* 12, 357–370.

Stambaugh, Robert F., 1986, Biases in regressions with lagged stochastic regressors, Working Paper No. 156, Graduate School of Business, University of Chicago.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Stock, James H., and Mark W. Watson, 1999, Forecasting inflation, *Journal of Monetary Economics* 44, 293–335.

Stock, James H., and Mark W. Watson, 2003, Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* 41, 788–829.

Stock, James H., and Mark W. Watson, 2004, Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting* 23, 405–430.

Timmermann, Alan, 2006, Forecast combinations, in Graham Elliott, Clive W.J. Granger, and Allan Timmermann, eds., *Handbook of Economic Forecasting* (Elsevier, Amsterdam).

Timmermann, Alan, 2008, Elusive return predictability, *International Journal of Forecasting* 24, 1–18.

Valkanov, Rossen, 2003, Long-horizon regressions: Theoretical results and applications, *Journal of Financial Economics* 68, 201–232.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

West, Kenneth D., 1996, Asymptotic inference about predictive ability, *Econometrica* 64, 1067–1084.

White, Halbert L., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica* 48, 817–838.

Xu, Yexiao, 2004, Small levels of predictability and large economic gains, *Journal of Empirical Finance* 11, 247–275.

Table I
Summary statistics

The table reports sample means and standard deviations (in percentage points) for excess returns on various portfolios and economic variables for 1996:07–2009:06. Sharpe ratios are also reported for the excess returns. All excess returns are computed relative to the risk-free rate. Panel A reports summary statistics for the China A-share aggregate value-weighted market portfolio (MKT). Panel B reports summary statistics for 13 valued-weighted industry portfolios. Panel C (D; E) reports summary statistics for 10 portfolios sorted on market capitalization (book-to-market value; Ownership-Concentration); S1,...,S10 (BM1,...,BM10; OC1,...,OC10) delineate deciles in ascending order for portfolios formed on market capitalization (book-to-market value; percentage of share held by the largest shareholder). Panel F reports summary statistics for 9 economic variables.

Variable	Mean	Std. dev.	Sharpe ratio	Variable	Mean	Std. dev.	Sharpe ratio	Variable	Mean	Std. dev.	Sharpe ratio
Panel A: Aggregate market portfolio excess returns											
MKT	1.26	9.01	0.14								
Panel B: Industry portfolio excess returns											
AGRIC	1.29	10.90	0.12	TRANS	1.35	9.50	0.14	SRVC	1.32	10.02	0.13
MINES	2.33	10.87	0.21	INFTK	1.49	11.52	0.13	MEDIA	1.25	12.11	0.10
MANUF	1.22	9.57	0.13	WHTSL	1.38	9.97	0.14	MULTP	1.31	10.89	0.12
UTILS	1.12	9.25	0.12	MONEY	1.58	10.59	0.15				
CNSTR	0.65	10.07	0.06	PROPT	1.39	10.31	0.13				
Panel C: Size portfolio excess returns											
S1	2.62	11.83	0.22	S6	1.47	10.43	0.14				
S2	2.02	11.25	0.18	S7	1.34	10.17	0.13				
S3	2.00	11.10	0.18	S8	1.29	9.95	0.13				
S4	1.84	10.68	0.17	S9	1.36	9.67	0.14				
S5	1.57	10.62	0.15	S10	0.99	8.78	0.11				
Panel D: Book-to-market portfolio excess returns											
BM1	0.60	9.83	0.06	BM6	1.24	9.28	0.13				
BM2	1.21	9.27	0.13	BM7	1.43	10.06	0.14				
BM3	1.04	9.22	0.11	BM8	1.61	10.32	0.16				
BM4	0.99	8.87	0.11	BM9	1.64	9.68	0.17				
BM5	1.40	9.79	0.14	BM10	1.70	10.31	0.16				
Panel E: Ownership-concentration portfolio excess returns											
OC1	1.33	9.41	0.14	OC6	1.09	9.10	0.12				
OC2	1.25	10.67	0.12	OC7	1.34	9.60	0.14				
OC3	1.47	10.57	0.14	OC8	1.12	9.33	0.12				
OC4	1.41	9.98	0.14	OC9	1.11	9.42	0.12				
OC5	1.33	9.58	0.14	OC10	1.46	8.74	0.17				
Panel F: Economic variables											
D/P	−4.64	0.54		B/M	0.34	0.13					
D/Y	−4.63	0.54		INF	0.001	0.01					
D/E	−1.04	0.29		NTIS	0.04	0.01					
SVAR	0.01	0.01		TO	0.12	0.08					
E/P	−3.60	0.44									

Table II
In-sample predictive regression results for industry portfolio excess returns with 9 economic variables as predictors

The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1996:07-2009:06;"*" indicates significance at the 5% level."Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading."Avg.R^2"is the row or column average of the R^2_{OS} statistics; the row average exclude MKT.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	Avg.R^2
MKT	2.02	2.28*	1.25	0.80	1.64	1.38	1.70*	1.28	2.98*	
	2.58	3.28	1.01	0.41	1.72	1.23	1.85	1.06	5.46	2.06
AGRIC	1.17	1.27	0.20	2.02*	1.31	0.59	1.09	1.40	3.08*	
	0.88	1.04	0.03	2.59	1.10	0.23	0.76	1.26	5.80	1.52
MINES	0.85	1.09	0.45	0.22	0.74	0.90	1.68*	1.54	1.95*	
	0.46	0.76	0.13	0.03	0.36	0.52	1.80	1.52	2.40	0.89
MANUF	2.18	2.38*	1.16	0.95	1.90	1.61	1.31	1.32	2.73*	
	2.98	3.55	0.86	0.58	2.28	1.65	1.10	1.12	4.61	2.08
UTILS	1.33	1.44	1.07	1.31	0.92	0.73	1.77*	1.18	2.55*	
	1.13	1.33	0.74	1.10	0.54	0.34	1.99	0.90	4.04	1.35
CNSTR	1.85	1.84*	1.17	1.36	1.49	1.39	1.73*	2.28*	1.41	
	2.18	2.16	0.89	1.19	1.43	1.23	1.90	3.26	1.27	1.72
TRANS	1.21	1.53	0.99	0.99	0.83	0.55	2.46*	0.71	3.29*	
	0.94	1.50	0.63	0.64	0.44	0.19	3.79	0.32	6.56	1.67
INFTK	1.18	1.40	0.07	1.42	1.41	1.00	0.95	0.86	2.32*	
	0.90	1.26	0.00	1.29	1.28	0.64	0.59	0.47	3.39	1.09
WHTSL	1.93	2.14*	0.66	1.04	1.94	1.54	0.85	1.60	2.65*	
	2.37	2.88	0.28	0.70	2.38	1.52	0.47	1.64	4.37	1.85
MONEY	2.62*	2.76*	1.99*	0.59	1.88	1.89	1.81*	1.08	2.52*	
	4.27	4.70	2.50	0.22	2.24	2.28	2.08	0.76	3.96	2.56
PROPT	2.70*	3.03*	1.31	1.08	2.42*	1.96	1.51	1.20	3.69*	
	4.50	5.62	1.11	0.75	3.67	2.42	1.45	0.93	8.14	3.18
SRVC	2.08	2.37*	0.62	1.11	2.14	1.76	1.19	1.40	2.75*	
	2.73	3.51	0.25	0.79	2.90	1.97	0.91	1.25	4.68	2.11
MEDIA	1.67	1.69	0.42	0.95	1.78	1.56	−0.32	1.50	1.51	
	1.77	1.81	0.11	0.59	2.01	1.56	0.07	1.44	1.46	1.20
MULTP	2.00	2.15*	0.53	1.29	2.11	1.61	1.26	1.09	2.58*	
	2.53	2.90	0.18	1.07	2.82	1.65	1.01	0.77	4.15	1.90
Sig.(5%)	2	7	1	1	1	0	5	1	11	
Avg. R^2	2.13	2.54	0.59	0.89	1.80	1.25	1.38	1.20	4.22	

Table III
In-sample predictive regression results for size portfolio excess returns with 9 economic variables as predictors

The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1996:07-2009:06;"*" indicates significance at the 5% level."Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading."Avg.R^2"is the row or column average of the R^2_{OS} statistics; the row average exclude MKT.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	Avg.R^2
MKT	2.02	2.28*	1.25	0.80	1.64	1.38	1.70*	1.28	2.98*	
	2.58	3.28	1.01	0.41	1.72	1.23	1.85	1.06	5.46	2.06
S1	0.51	0.76	−0.67	1.98*	1.08	0.10	0.87	1.41	3.31*	
	0.17	0.37	0.29	2.48	0.75	0.01	0.49	1.28	6.65	1.39
S2	1.21	1.41	−0.29	1.83*	1.69	0.88	0.67	1.33	2.81*	
	0.94	1.27	0.05	2.14	1.83	0.50	0.29	1.14	4.87	1.45
S3	1.28	1.49	0.04	2.02*	1.56	0.79	1.33	1.41	3.30*	
	1.06	1.41	0.00	2.57	1.55	0.40	1.13	1.27	6.59	1.78
S4	1.47	1.71	0.18	1.75*	1.70	0.98	1.00	1.33	3.22*	
	1.39	1.86	0.02	1.94	1.85	0.62	0.65	1.13	6.32	1.75
S5	1.70	1.91*	0.18	1.54	1.98	1.28	1.04	1.17	3.00*	
	1.83	2.32	0.02	1.52	2.47	1.06	0.70	0.88	5.51	1.81
S6	1.78	1.97*	0.38	1.84*	1.94	1.31	1.17	1.36	3.09*	
	2.01	2.47	0.09	2.15	2.38	1.11	0.87	1.19	5.85	2.01
S7	2.05	2.28*	0.77	1.45	2.01	1.56	1.34	1.23	3.03*	
	2.65	3.26	0.38	1.35	2.55	1.56	1.16	0.98	5.63	2.17
S8	2.13	2.35*	0.98	1.26	1.96	1.61	1.29	1.30	2.83*	
	2.86	3.46	0.63	1.01	2.43	1.66	1.07	1.09	4.94	2.13
S9	2.33*	2.58*	1.22	1.07	2.04	1.66	1.50	1.22	3.16*	
	3.39	4.16	0.96	0.74	2.62	1.75	1.44	0.96	6.08	2.45
S10	2.48*	2.69*	2.05*	0.21	1.67	1.74	1.91*	0.92	2.37*	
	3.85	4.49	2.67	0.03	1.77	1.93	2.32	0.55	3.53	2.35
Sig.(5%)	2	6	1	5	0	0	1	0	10	
Avg. R^2	2.02	2.51	0.51	1.59	2.02	1.06	1.01	1.05	5.60	

Table IV
In-sample predictive regression results for book-to-market portfolio excess returns with 9 economic variables as predictors

The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1996:07-2009:06;"*"indicates significance at the 5% level."Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading."Avg.R^2"is the row or column average of the R^2_{OS} statistics; the row average exclude MKT.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	Avg.R^2
MKT	2.02	2.28*	1.25	0.80	1.64	1.38	1.70*	1.28	2.98*	
	2.58	3.28	1.01	0.41	1.72	1.23	1.85	1.06	5.46	2.06
BM1	2.01	2.26*	0.90	0.95	1.87	1.51	1.19	1.27	2.79*	
	2.55	3.21	0.53	0.58	2.21	1.46	0.91	1.03	4.82	1.92
BM2	2.05	2.24*	0.74	1.06	2.03	1.79	0.96	1.20	2.93*	
	2.66	3.16	0.36	0.72	2.60	2.04	0.59	0.93	5.28	2.04
BM3	1.95	2.30*	1.09	0.70	1.66	1.38	1.27	1.20	3.37*	
	2.40	3.33	0.77	0.32	1.76	1.23	1.04	0.92	6.88	2.07
BM4	1.93	2.17*	1.16	0.68	1.60	1.44	1.59	1.87	2.40*	
	2.36	2.96	0.87	0.30	1.63	1.34	1.62	2.21	3.61	1.88
BM5	1.50	1.81	0.77	1.09	1.33	0.93	1.67*	1.20	3.05*	
	1.44	2.09	0.39	0.76	1.13	0.56	1.79	0.93	5.70	1.64
BM6	1.74	1.91*	0.88	0.76	1.55	1.26	1.27	1.42	2.21*	
	1.93	2.32	0.50	0.37	1.54	1.02	1.03	1.28	3.06	1.45
BM7	1.76	2.04*	1.24	0.74	1.33	0.99	1.90*	1.24	2.97*	
	1.97	2.64	0.99	0.36	1.13	0.63	2.29	0.98	5.43	1.83
BM8	1.96	2.24*	1.14	0.91	1.65	1.33	1.42	0.83	2.84*	
	2.44	3.16	0.84	0.53	1.73	1.13	1.30	0.44	4.97	1.84
BM9	1.83	2.14*	1.36	0.63	1.35	1.07	1.99*	1.06	2.73*	
	2.14	2.88	1.18	0.25	1.16	0.73	2.51	0.73	4.61	1.80
BM10	2.09	2.31*	1.41	0.67	1.62	1.37	1.54	0.85	2.59*	
	2.77	3.35	1.28	0.29	1.68	1.20	1.52	0.47	4.17	1.86
Sig.(5%)	0	9	0	0	0	0	3	0	10	
Avg. R^2	2.27	2.91	0.77	0.45	1.66	1.13	1.46	0.99	4.85	

Table V
In-sample predictive regression results for ownership-concentration portfolio excess returns with 9 economic variables as predictors

The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the largest shareholder share holding percentage-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. OC1,...,OC10 delineate deciles in ascending order for portfolios formed on largest shareholder share holding percentage. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1996:07-2009:06;"*" indicates significance at the 5% level."Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading."Avg.R^2"is the row or column average of the R^2_{OS} statistics; the row average exclude MKT.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	Avg.R^2
MKT	2.02	2.28*	1.25	0.80	1.64	1.38	1.70*	1.28	2.98*	
	2.58	3.28	1.01	0.41	1.72	1.23	1.85	1.06	5.46	2.06
OC1	2.31*	2.61*	1.35	0.89	1.93	1.65	1.48	1.14	3.17*	
	3.35	4.24	1.17	0.51	2.35	1.74	1.39	0.83	6.11	2.41
OC2	1.71	2.00*	0.77	0.90	1.59	1.21	1.22	0.98	3.10*	
	1.86	2.52	0.38	0.53	1.61	0.94	0.96	0.62	5.89	1.70
OC3	1.68	1.97*	0.56	1.42	1.69	1.01	1.49	0.90	3.45*	
	1.79	2.45	0.21	1.29	1.82	0.66	1.42	0.52	7.17	1.93
OC4	2.23	2.47*	0.93	1.34	2.12	1.64	1.18	1.48	3.24*	
	3.13	3.80	0.56	1.16	2.84	1.71	0.89	1.41	6.40	2.43
OC5	1.94	2.20*	0.99	1.42	1.72	1.33	1.35	1.20	3.27*	
	2.38	3.06	0.64	1.29	1.88	1.14	1.17	0.93	6.50	2.11
OC6	1.40	1.69	0.72	0.39	1.25	0.90	1.74*	1.21	2.50*	
	1.26	1.82	0.34	0.10	1.00	0.53	1.92	0.94	3.90	1.31
OC7	2.45*	2.63*	1.43	0.75	2.05	1.84	1.87*	1.31	2.47*	
	3.76	4.30	1.31	0.36	2.66	2.15	2.23	1.10	3.82	2.41
OC8	2.02	2.26*	1.02	1.45	1.80	1.42	1.48	0.83	3.08*	
	2.58	3.22	0.67	1.34	2.06	1.30	1.40	0.45	5.80	2.09
OC9	1.95	2.20*	1.15	0.72	1.62	1.38	1.48	0.98	2.67*	
	2.41	3.06	0.86	0.33	1.68	1.22	1.40	0.62	4.44	1.78
OC10	1.91	2.15*	1.51	0.16	1.34	1.44	1.65*	1.54	2.25*	
	2.32	2.90	1.45	0.02	1.16	1.32	1.75	1.52	3.19	1.74
Sig.(5%)	2	9	0	0	0	0	3	0	10	
Avg. R^2	2.48	3.14	0.76	0.69	1.91	1.27	1.45	0.89	5.32	

Table VI
Out-of-sample predictive regression results for industry portfolio excess returns with 9 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 2002:01–2009:06 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports out-of-sample results for the excess return on the China A-Share aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 9 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent ; "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	COMBINE
MKT	0.30	0.98	1.84	−2.01	−4.78	−7.13	0.76	1.23	7.79*	3.13*
AGRIC	−2.04	−1.88	0.45	−1.22	−6.48	−7.54	0.43	−0.23	4.90	2.72*
MINES	−1.07	−0.97	−2.99	−1.88	−4.34	−7.60	0.77	2.08	3.48*	3.03*
MANUF	1.34	2.08	1.69	−1.05	−2.78	−4.48	0.04	1.41	6.11*	2.84*
UTILS	−1.19	−1.37	0.77	−1.07	−3.84	−4.89	1.01	0.29	4.91*	2.53*
CNSTR	2.88*	3.04*	1.53*	0.74	0.60	−0.04	−0.55	5.49*	−0.49	2.74*
TRANS	−3.44	−3.71	0.45	−3.46	−8.68	−10.99	1.40	−1.07	8.95*	5.04*
INFTK	−5.30	−6.14	0.77	−2.02	−13.39	−19.35	−2.22	−1.20	6.99*	4.76*
WHTSL	1.35	2.07	0.17	−0.81	−2.06	−3.96	−0.33	2.64	5.63*	2.97*
MONEY	1.39	2.87*	2.37	−4.52	−2.50	−4.38	1.99	−2.65	5.69*	4.21*
PROPT	3.00*	3.74*	1.34	−1.19	0.06	−1.77	−1.27	0.56	9.44*	4.12*
SRVC	3.17*	3.55*	−0.09	−1.69	−0.04	−2.24	−1.09	2.38	6.11*	4.29*
MEDIA	−0.01	0.37	0.08	−0.22	−4.33	−8.75	−0.15	2.41*	0.98	1.39*
MULTP	0.14	0.26	0.38	−0.72	−4.62	−8.46	−0.65	0.42	5.74*	2.30*

Table VII
Out-of-sample predictive regression results for size portfolio excess returns with 9 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 2002:01–2009:06 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports out-of-sample results for the excess return on the China A-Share aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 9 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent ; "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	COMBINE
MKT	0.30	0.98	1.84	−2.01	−4.78	−7.13	0.76	1.23	7.79*	3.13*
S1	−3.03	−2.05	1.17	1.66	−6.79	−10.21	−2.03	1.66	9.71*	5.75*
S2	0.27	0.31	−0.26	0.99	−4.13	−7.21	−1.16	1.71	6.50*	2.93*
S3	−0.98	−0.84	0.23	0.53	−4.62	−6.67	−1.78	1.99	8.65*	4.33*
S4	−0.38	−0.19	0.04	0.15	−3.60	−5.76	−1.06	1.53	8.01*	3.59*
S5	−0.50	−0.64	0.19	−0.01	−4.00	−6.24	−0.78	0.63	6.94*	3.45*
S6	−0.30	−0.15	0.26	−0.06	−4.12	−6.83	−0.78	2.06	7.79*	4.16*
S7	0.27	0.68	0.80	−1.11	−3.91	−6.14	−0.37	0.60	7.17*	2.86*
S8	1.35	1.83	1.12	−0.94	−2.49	−4.29	−0.19	1.21	6.19*	3.11*
S9	0.55	1.20	1.39	−1.17	−3.94	−6.81	0.29	0.30	7.96*	3.00*
S10	2.05	3.33*	3.94*	−1.69	−3.45	−5.22	2.02*	−0.91	5.05*	4.31*

Table VIII
Out-of-sample predictive regression results for book-to-market portfolio excess returns with 9 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 2002:01–2009:06 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports out-of-sample results for the excess return on the China A-Share aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 9 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent ; "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	COMBINE
MKT	0.30	0.98	1.84	−2.01	−4.78	−7.13	0.76	1.23	7.79*	3.13*
BM1	1.38	2.38	1.59*	−1.17	−3.16	−5.67	0.39	1.68	7.26*	3.00*
BM2	1.29	2.05	0.42	−1.80	−3.39	−6.27	−0.36	0.30	7.91*	3.22*
BM3	0.40	1.48	1.37	−2.37	−5.21	−6.97	−0.15	1.80	9.31*	3.68*
BM4	1.93	2.73	1.49	−1.50	−3.33	−5.79	0.40	4.89*	5.13*	3.42*
BM5	−1.04	−0.85	0.78	−1.64	−5.14	−7.10	−0.31	1.30	8.00*	4.14*
BM6	0.71	1.28	0.97	−1.01	−3.83	−6.06	−0.70	2.01	4.08*	2.38*
BM7	−2.06	−1.77	0.80	−1.15	−6.71	−8.72	0.74	0.99	7.41*	3.38*
BM8	0.20	1.04	1.23	−1.68	−4.13	−6.24	0.07	−0.13	6.88*	2.89*
BM9	−0.73	−0.03	1.52	−1.91	−5.51	−7.79	1.95	0.51	5.75*	3.24*
BM10	−1.19	−1.18	1.67	−2.02	−5.75	−7.14	0.21	−2.36	5.64*	3.39*

Table IX
Out-of-sample predictive regression results for ownership-concentration portfolio excess returns with 9 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 2002:01–2009:06 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the largest shareholder share holding percentage-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports out-of-sample results for the excess return on the China A-Share aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 9 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent ; "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/P	D/Y	D/E	SVAR	E/P	B/M	INF	NTIS	TO	COMBINE
MKT	0.30	0.98	1.84	−2.01	−4.78	−7.13	0.76	1.23	7.79*	3.13*
OC1	1.55	3.03	1.88	−2.93	−3.18	−5.50	0.23	0.17	9.12*	3.65*
OC2	−0.92	−0.39	1.26	−1.57	−5.80	−8.22	−1.07	0.72	8.41*	4.20*
OC3	−2.98	−3.01	0.47	−1.09	−8.31	−11.45	−0.15	−1.00	10.37*	6.24*
OC4	−0.88	−0.36	0.77	−1.40	−5.92	−8.78	−0.34	1.70	8.47*	4.53*
OC5	−1.14	−0.83	1.52	−1.67	−6.85	−8.62	−0.20	0.67	9.46*	4.83*
OC6	0.98	1.39	0.35	−1.40	−3.43	−5.27	1.35	1.54	4.85*	2.23*
OC7	2.53	3.41*	1.95	−1.12	−1.95	−3.77	1.04	1.86	4.87*	3.51*
OC8	0.30	0.86	0.76	−1.08	−2.45	−4.82	0.44	−2.39	7.19*	2.81*
OC9	0.90	1.70	1.68	−1.42	−2.99	−4.67	0.29	0.55	6.13*	2.53*
OC10	0.94	1.43	1.77	−1.82	−3.89	−5.53	0.13	2.53	4.28*	2.72*

Table X

R^2_{OS} statistics computed over 02:01-06:12,07:01-09:06 and 02:01-09:09 forecast evaluation period for industry, size, book-to-market and ownership-concentration portfolio excess returns with 9 economic variables as predictors

The table reports R^2_{OS} statistics (in percent) for out-of-sample forecasts of industry (Panel B), size (Panel C), book-to-market (Panel D),and ownership-concentration (Panel E) portfolio excess returns for 1996:07–2009:06 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value;OC1,...,OC10 delineate deciles in ascending order for portfolios formed on largest shareholder share holding percentage). Results are reported for combination forecasts using 9 economic variables as predictors (see Tables VI, VII, VIII and IX). Panel A reports out-of-sample results for the excess return on the China A-share value-weighted portfolio. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 statistic. The "02:01-06:12" columns report R^2_{OS} statistics computed over 2002:01-2006:12 forecast evaluation period; the "07:01-09:06" columns report R^2_{OS} statistics computed over 2007:01-2009:06 forecast evaluation period;the "02:01-09:06" columns report R^2_{OS} statistics computed over 2002:01-2009:06 forecast evaluation period. The "Average" rows give the averages across the portfolios in the individual panels.

Return	02:01-06:12	07:01-09:06	02:01-09:06	Return	02:01-06:12	07:01-09:06	02:01-09:06	Return	02:01-06:12	07:01-09:06	02:01-09:06
Panel A: Aggregate market portfolio excess returns											
MKT	2.57	4.52	3.13								
Panel B: Industry portfolio excess returns											
AGRIC	5.11	2.37	2.72	TRANS	3.91	3.95	5.04	SRVC	2.79	4.02	4.29
MINES	7.84	3.22	3.03	INFTK	6.65	3.27	4.76	MEDIA	2.01	2.11	1.39
MANUF	2.62	3.16	2.84	WHTSL	3.02	3.10	2.97	MULTP	3.49	3.83	2.30
UTILS	2.86	2.36	2.53	MONEY	2.97	6.07	4.21				
CNSTR	2.25	2.45	2.74	PROPT	2.07	5.22	4.12				
Average	3.66	3.47	3.30								
Panel C: Size portfolio excess returns											
S1	8.91	3.23	5.75	S6	5.02	3.37	4.16				
S2	5.84	2.81	2.93	S7	3.13	3.27	2.86				
S3	7.13	2.92	4.33	S8	2.28	3.18	3.11				
S4	5.58	2.85	3.59	S9	2.33	3.65	3.00				
S5	4.93	3.07	3.45	S10	3.08	4.34	4.31				
Average	4.82	3.27	3.75								
Panel D: Book-to-market portfolio excess returns											
BM1	2.09	3.48	3.00	BM6	2.34	3.26	2.38				
BM2	2.47	3.45	3.22	BM7	2.85	3.96	3.38				
BM3	2.94	3.75	3.68	BM8	1.78	3.57	2.89				
BM4	2.31	4.25	3.42	BM9	1.17	4.18	3.24				
BM5	3.59	3.37	4.14	BM10	2.13	3.51	3.39				
Average	2.37	3.68	3.27								
Panel E: Ownership-concentration portfolio excess returns											
OC1	2.27	5.12	3.65	OC6	1.75	3.51	2.23				
OC2	3.55	2.87	4.20	OC7	2.38	3.72	3.51				
OC3	4.53	3.97	6.24	OC8	2.29	3.24	2.81				
OC4	3.35	3.68	4.53	OC9	1.33	3.18	2.53				
OC5	3.22	3.84	4.83	OC10	2.91	3.46	2.72				
Average	2.76	3.66	3.72								

Table XI

Conditional CAPM $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics for industry, size, book-to-market and ownership-concentration portfolio excess returns with 9 economic variables as predictors

The table reports $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics (in percent) for out-of-sample forecasts of industry (Panel A), size (Panel B), book-to-market (Panel C) and ownership-concentration (Panel D) portfolio excess returns for 2002:01-2009:06 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value;OC1,...,OC10 delineate deciles in ascending order for portfolios formed on largest shareholder share holding percentage). Results are reported for combination forecasts using 9 economic variables as predictors (see Tables VI, VII, VIII and IX). $R^2_{OS,R}$ ($R^2_{OS,\alpha}$) measures the reduction in mean square prediction error for the rational pricing-restricted combination forecast based on the conditional CAPM relative to the historical average combination forecast (unrestricted combination forecast relative to the rational pricing-restricted combination forecast). "*" indicates that $R^2_{OS,R}$ or $R^2_{OS,\alpha}$ is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
			Panel A: Industry portfolio excess returns					
AGRIC	2.05*	0.68	TRANS	3.36*	1.74	SRVC	2.46*	1.88*
MINES	1.26	1.79	INFTK	2.39*	2.43*	MEDIA	1.60*	−0.22
MANUF	2.77*	0.07	WHTSL	2.44*	0.55	MULTP	2.71*	−0.42
UTILS	2.98*	−0.46	MONEY	2.06*	2.20*			
CNSTR	3.16*	−0.44	PROPT	2.79*	1.37*			
			Panel B: Size portfolio excess returns					
S1	4.78*	1.03	S6	2.76*	1.44			
S2	3.01*	−0.09	S7	2.56*	0.31			
S3	3.35*	1.02	S8	2.54*	0.59			
S4	2.87*	0.74	S9	2.76*	0.25			
S5	2.74*	0.73	S10	3.54*	0.80			
			Panel C: Book-to-market portfolio excess returns					
BM1	2.87*	0.13	BM6	2.59*	−0.22			
BM2	2.49*	0.75*	BM7	2.88*	0.51			
BM3	2.96*	0.75*	BM8	2.55*	0.35			
BM4	2.98*	0.46	BM9	2.75*	0.50			
BM5	3.14*	1.03	BM10	2.54*	0.88			
			Panel D: Ownership-concentration portfolio excess returns					
OC1	2.95*	0.72*	OC6	3.04*	−0.83			
OC2	2.82*	1.42*	OC7	2.90*	0.63*			
OC3	3.34*	3.00*	OC8	2.86*	−0.05			
OC4	2.84*	1.74*	OC9	2.97*	−0.46			
OC5	3.14*	1.75*	OC10	2.11*	0.63			

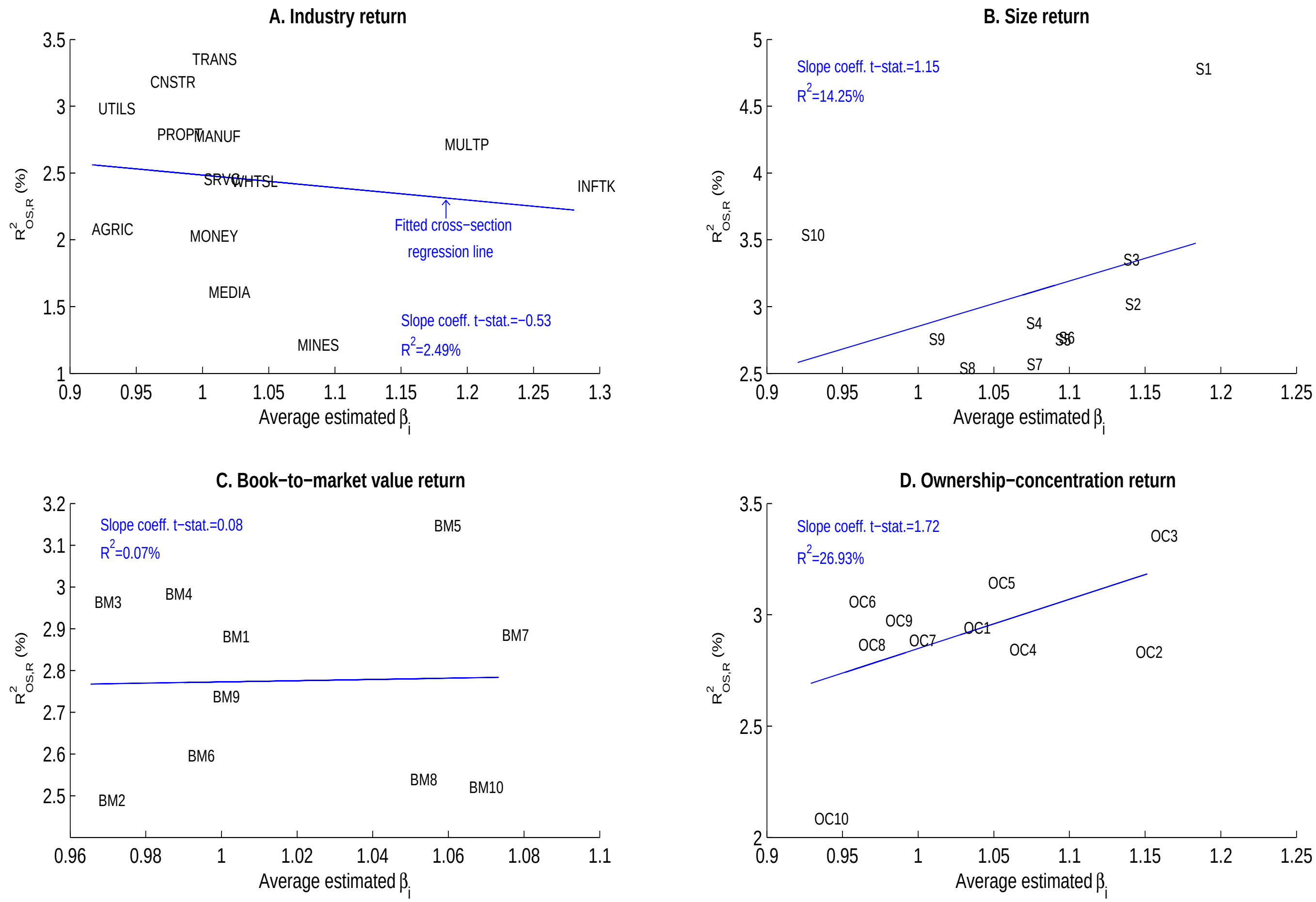

Figure 1. Relationship between $R^2_{OS,R}$ statistics and average estimated betas. Each panel contains a scatterplot relating the $R^2_{OS,R}$ statistics in Tables XI to the average estimated β_i used to generate rational pricing-restricted combination forecasts over 2002:01–2009:06. Each panel includes a fitted regression line and regression results for a cross-section regression model with $R^2_{OS,R}$ as the regress and and average estimated β_i as the regressor (an intercept term is included in the cross-section regression model).

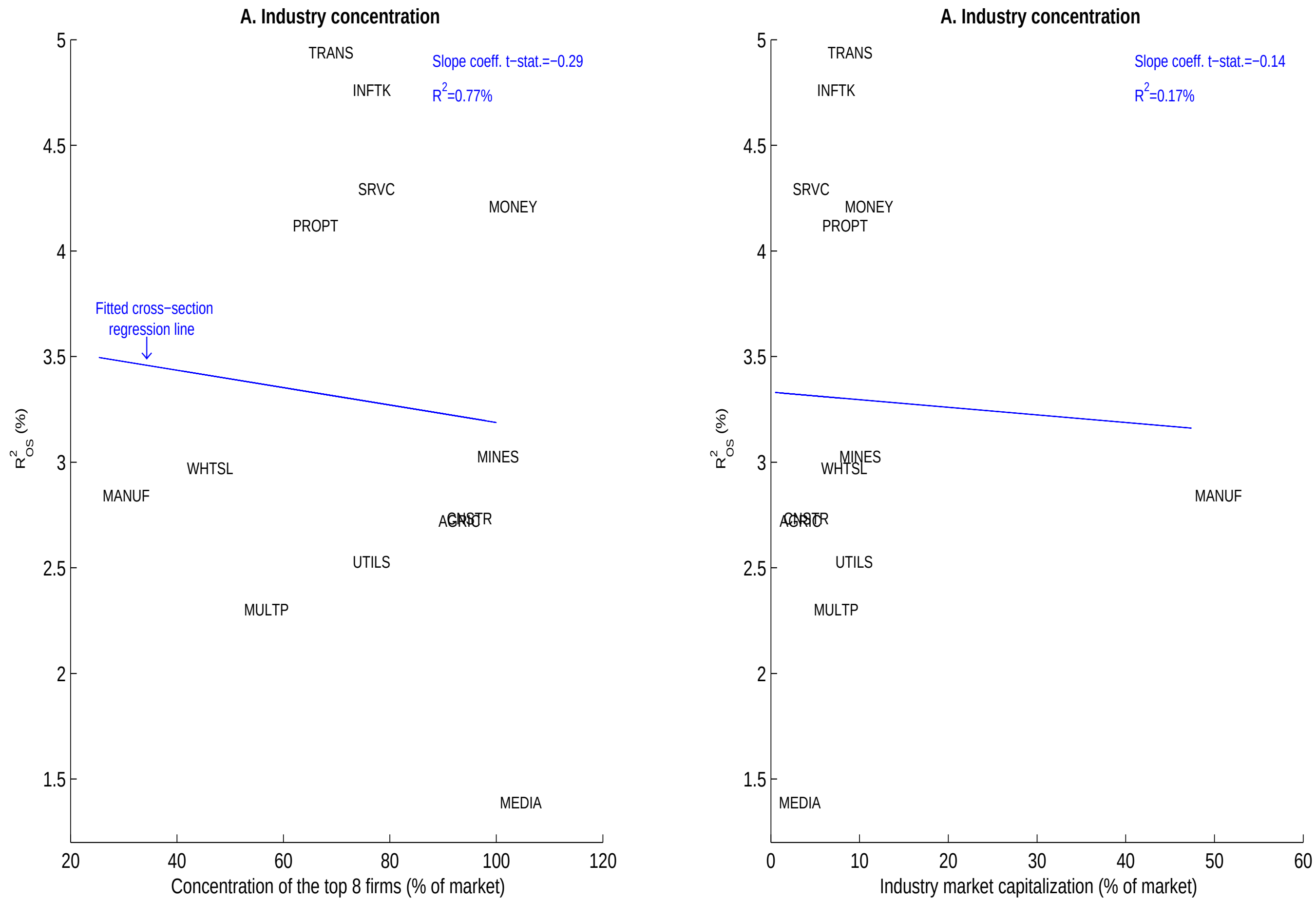

Figure 2. Relationship between industry concentration or market capitalization and R^2_{OS} statistics for industry portfolio excess returns. Each panel contains a scatterplot relating the R^2_{OS} statistics in Table IX to industry concentration (average market share of the eight largest firms) and market capitalization in Panels A and B, respectively. Each panel includes a fitted regression line and regression results for a cross-section regression model with R^2_{OS} as the regressand and industry concentration or market capitalization as the regressor (an intercept term is included in the cross-section regression model).