

Stock Return Synchronicity and Technical Trading Rules

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ABSTRACT

We explore the potential *source* of returns from technical trading rules at the *firm-level* by examining the *cross-sectional* relationship between technical trading returns and stock return synchronicity. Inspired by Roll (1988) and Morck, Yeung and Yu (2000), we use R^2 of a regression of individual stock returns on the market return as our measure of synchronicity. If a low R^2 is largely attributable to noise trading, stocks will have lower synchronicity with market factors and lower R^2 . Low R^2 stocks earn *higher* expected returns, according to De Long, Shleifer, Summers, and Waldmann (1989, 1990), or due to limits of arbitrage (Shleifer and Vishny, 1997), a predicted relationship which we termed as the *Noise Hypothesis*. Overwhelming support in prior literature is in favor of *lower* expected returns in low R^2 stocks, or the *Price-Informativeness Hypothesis* according to Morck, Yeung and Zarowin (2003). China is our context for investigation; it is the second most synchronous market in the study by Morck et al (2000) which has grown to become the world's third largest stock market by market capitalization. We find evidence of a *negative* relationship between returns from technical trading rules and R^2 over 1991-2009, in favor of the *Noise Hypothesis*. Our results remain robust after controlling for firm-specific characteristics which include market-to-book, size, leverage, dividend payout ratio, turnover and firm age. Thus, an additional simple yet practical statistics - the R^2 - can guide trading decisions using technical trading rules. Do technical trading rules work? Possibly only when the R^2 is low, and for *larger* and *younger* stocks with *lower* turnover. However, sub-period analysis reveal that when there is an improvement in the information environment after the punctuation by an economically significant fundamental shock - the Non-Tradable Share (NTS) reform in China in April 2005 - technical analysis work better post-NTS reform during 2005-09 for stocks with *higher* R^2 , consistent with the *Price-Informativeness Hypothesis*, and generally for *older* and bigger stocks with lower turnover and higher market-to-book ratio. Thus, without the guide of R^2 , investors should take the market prognosis by all these "alchemists" with their "voodoo" charts with a heavy dose of salt. We also reconciled the lively debate and extremely mixed evidence on the *interpretation* of R^2 and its relationship with the cross-sectional returns of stocks.

JEL classification: G11, G12, G14, G15, C1, O16, O53

Keywords: Stock return synchronicity, R^2 , idiosyncratic volatility, technical trading rules, price informativeness, noise

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1. INTRODUCTION AND MOTIVATION

Few departures in position in finance are as vexing as that of establishing consistent and reliable returns predictability from past returns using technical trading rules and chart patterns across markets and over time. While technical analysis, ridiculed as “alchemy” by Burton Malkiel in his 1973 book “A Random Walk Down Wall Street”, challenges the formidable market efficiency orthodoxy (Fama, 1970), there is pervasive use by practitioners and the persistence of belief in technical analysis techniques (see survey studies in Park and Irwin, 2007, and Menkhoff and Taylor, 2007). However, the intellectual vacuum at the core of technical analysis – that efficient markets remove possible short-term patterns and autocorrelations in stock returns - has been increasingly filled up in recent times by growing receptiveness that markets may not be fully efficient because of noise trading (Kyle, 1985; Black, 1986), that herding behavior of short-horizon traders can result in informational inefficiency (Froot, Scharfstein and Stein, 1992) and self-fulfilling tendencies (Frankel and Froot, 1990), and that prices may be affected by behavioural biases (Barberis, Schleifer and Vishny, 1998; Daniel, Kent, Hirshleifer and Subrahmanyam, 1998; Hirshleifer, 2001; Shiller, 2003). Such peripheral views get reinforced the more difficult market conditions are, when techniques based on profits and valuations failed (Talley, 2002), especially during the recent financial crisis (Avgouleas, 2009), and with the growing influence of quantitative hedge funds that employ the automation of technical trading rules as one of their investment strategies (Lo and Hasanhodzic, 2009). Still, the profitability of using technical trading rules based on past prices remains an open empirical question, albeit an extensively examined one.

We tread a different path in our study by exploring the potential *source* of the returns of technical trading rules at the *firm-level*, an issue that has not been commonly explored in prior studies. We are motivated to examine this because of the parallel observation of a reported decline in technical trading profitability in U.S. over time (Sullivan, Timmermann and White, 1999; LeBaron, 2000; Kwon and Kish, 2002; Ready, 2002; Schulmeister, 2009), and a lower synchronicity of U.S. stock prices, or higher idiosyncratic volatility of individual firms, over time as the U.S. economy developed (Morck, Yeung and Yu, 2000, hereafter termed MYY).

The popular explanation for this profitability decline in deploying technical trading rules is that markets have become more efficient and hence such opportunities have disappeared. This is especially so with the advent of cheaper computing power to spark the proliferation of computer-driven trading, the growth of electronic communication networks (ECNs) that allow thousands of buy and sell orders to be matched at the speed of light without any human intervention¹; the increasing popularity of “dark pool” platform where buyers and sellers can anonymously match large blocks of stock and keep details of the deals and prices concealed to prevent distorting prices in the broader

¹ According to the New York Stock Exchange daily public disclosure, program trading accounts for about 20-25% and as high as 80% of the trading volume on that exchange every day.

market; and the lower transaction costs; all of which are helping to remove possible short-term patterns and autocorrelations in stock returns.

Similar to MYY, Campbell, Lettau, Malkiel and Xu (CLMX, 2001) also found a secular decline in stock return synchronicity in the United States from 1960 to 1997, but they do not link it to cross-sectional returns. This time-series observation suggests that there could be a *cross-sectional* relationship between technical trading profitability and stock return synchronicity at the *firm-level*. Thus, the source of the profitability (or losses) of technical trading rules could be due to varying degrees of firm-level synchronicity with the market, a relationship that has not been explored in prior literature.

We like to emphasize that our study is more concerned about investigating the source of the returns from the technical trading rules by testing its association with stock return synchronicity, rather than focusing on establishing the highly contentious point of whether the technical trading rules are indeed profitable and robust to problems such as data-snooping biases (Sullivan, Timmerman and White, 1999), since we acknowledge that these trading rules might perhaps *not* work for *certain* stocks at the firm-level, and we want to know what are the predictors that determine the trading profits or losses from applying these technical rules.

Inspired by Roll (1988), MYY is the first in a series of papers that uses the R^2 of a regression of individual stock returns on the market return as a measure of synchronicity, or the extent to which the stock prices of individual firms within a country move together. R^2 is also the ratio of idiosyncratic volatility to systematic volatility; idiosyncratic volatility is thus the *inverse* measure of synchronicity. In sum, *lower* R^2 , or *higher* idiosyncratic volatility of individual firms, indicates *lower* synchronicity of stock returns. Roll (1988) offers an interesting discussion of R^2 , observing that the low R^2 statistics among U.S. stocks and for common asset pricing models is due to vigorous firm-specific return variation not associated with identifiable news releases and public information. He concludes that this implies “either private information or else occasional frenzy unrelated to concrete information (noise)”. The incorporation of either firm-specific information or noise both result in a lower R^2 , but these two effects lead to starkly *different* predictions of the relation between R^2 and expected stock returns:

- (a) The *Price-Informativeness Hypothesis*: If a *low* R^2 is largely resulted from the firm’s environment causing the stock prices to aggregate more firm-specific information, greater firm-specific uncertainty is resolved such that market factors should explain a smaller proportion of the variation in stock returns, increasing the realized historical idiosyncratic volatility, and investors holding these stocks should require *lower* expected returns.
- (b) The *Noise Hypothesis*: If a *low* R^2 is largely attributable to the trading by noise traders, stocks will have lower synchronicity with market factors and lower R^2 because the changes in stock prices cannot be fully justified by changes in fundamental risks reflected in the common

factors, and investors should earn *higher* expected returns according to De Long, Shleifer, Summers, and Waldmann (1989, 1990).

Both finance and accounting research had tilted *overwhelmingly* in favor of the *Price-Informativeness Hypothesis*, in that R^2 or stock return synchronicity is a measure for how much private information is impounded into stock prices. When informed trading activity is generated, it contributes to the lower R^2 (or increase in idiosyncratic volatility). This is in the spirit of the Grossman and Stiglitz (1980) argument who predict that improving the cost-benefit trade-off on private information collection leads to more extensive informed trading and to more informative pricing. In a market with many risky stocks, the ones with cheaper information about their fundamental values are more attractive to traders. Accordingly, traders acquire more information about these stocks and their prices are more volatile and more informative than the prices of stocks with more costly information. Private information is turned into public information, thereby reducing the adverse selection problem of uninformed investors trading with informed investors.

At the *country-level*, MYY (2000) find that stock prices are more synchronous (i.e. have higher R^2) in emerging markets which are low-income countries with weak protection of investors' and property rights; weak institutions discourage the acquisition of information about individual stocks and such markets lack informed traders because risk arbitrageurs find it more costly to keep their profits in such economies. However, there are mixed results when the country-level findings are examined at the *firm-level*. On one hand, Durnev, Morck, Yeung and Zarowin (2003) find evidence that firm with lower R^2 exhibit higher associations between current returns and future earnings, suggesting that lower R^2 is indicative of better informationally-efficient prices. Piotroski and Roulstone (2004) find that both institutional and insider trading are positively associated with idiosyncratic volatility. In other words, stocks with higher institutional trading and insider trading have lower R^2 , since institutional trading accelerates the incorporation of firm-specific information into stock prices, and consequently, lowers R^2 .

On the other hand, in a widely-cited paper, Ang, Hodrick, Xing, and Zhang (2006) report that stocks with low R^2 (or high idiosyncratic volatility) is associated with "abysmally low returns". The average differential between quintile value-weighted portfolios of the lowest and highest idiosyncratic volatility is about -1.06 percent per month. Ang (2009) also confirm that the link also exists in 23 other developed markets. The *Noise Hypothesis* is originated by Shiller (1981) who finds that the level of stock price volatility is too high to be explained by the volatility in the underlying fundamentals, e.g. dividends. Other studies suggest that behavioural factors, bubbles, herding, and other non-fundamental factors affect stock return volatility (see Shleifer (2000) for a review), and ultimately the usefulness of the synchronicity measure as a gauge of firm-specific information. Behavioural models, like Barberis and Huang (2001) predict that lower R^2 stocks earn higher expected returns. In environments with frictions and incomplete information (Merton, 1987) and

limits to arbitrage (Shleifer and Vishny, 1997), R^2 (or the idiosyncratic volatility of a stock) is linked to its expected return.

Thus, if there is a *cross-sectional* relationship between technical trading profitability and stock return synchronicity, the direction is *unclear* due to the two competing hypotheses.

Still, the U.S. ranks as having the *lowest* synchronicity amongst the 40 countries in MYY (2000) study and there might not be a great deal of cross-sectional variation in synchronicity at the firm-level. China is the *second most synchronous* market in 1995 in MYY (2000) study, where over 80 percent of stocks often move in the same direction in a given average week. There are also several important stylized facts about China that made it an economically important ground for investigation. China's GDP per capita was \$455 in 1995 in the MYY (2000) study and has since surged more than 14-fold to \$6,546 in 2009. While it is still an "emerging market" and "low-income country", Shanghai has the world's third largest stock market by market capitalization at around \$3 trillion in its \$3.2 trillion economy, briefly overtaking Tokyo in July 2009. Shares worth \$5.01 trillion changed hands on the Shanghai Stock Exchange in 2009, compared with \$4.07 trillion on the Tokyo Stock Exchange, according to data compiled by Bloomberg. Only the NASDAQ stock market and the New York Stock Exchange had higher trading volumes than Shanghai. As an emerging market, China has a very high ratio of stocks changing hands. Wong (2006) reported that the turnover velocity of stocks, defined as the total transaction volume divided by the total number of tradable shares, was about 500 percent, suggesting the prevalence of noise trading in China. Moreover, some countries, including China, place asymmetric restrictions on the price formation process, such as short-selling constraints, which impede the impounding of bad news into prices in a timely manner and contribute to the high co-movement of stock prices (Miller, 1977; Bris, Goetzmann and Zhu, 2003). Jin and Myers (2006) find that such synchronous markets are more prone to crashes.

Using a comprehensive sample of China stocks since the inception of the Shanghai Exchange in January 1991 to December 2009, we show that the returns from technical trading rules has a *negative* association with stock return synchronicity, or the R^2 . Thus, we find evidence in favor of the *Noise Hypothesis* in that stocks with *lower* R^2 earn *higher* profits from technical trading rules. Ranking the sample into 10 decile portfolios by R^2 , we find that the technical trading returns in N1 (lowest R^2 portfolio) exceeds that in N10 (highest R^2 portfolio) by an annualized 7-11 percent over the sample period, depending on the type of technical trading rule that is employed. Our results remain robust even after controlling for firm-specific characteristics which include market-to-book, size, leverage, dividend payout ratio, turnover and firm age.

Thus, an additional simple yet practical statistics - the R^2 - can guide trading decisions using technical trading rules. Imagine that the Bloomberg terminal, Yahoo Finance and financial websites should have an additional statistics – the synchronicity measure – to allow investors and traders to assess how effective their technical analysis can be; for instance, if the informational environment is

generally noisy, then the technical traders should focus their efforts on less synchronous or low R^2 stocks to increase their probability of generating abnormal profits.

Do technical trading rules work? Possibly only when the R^2 is low, and for *larger* and *younger* stocks with *lower* turnover. However, sub-period analysis reveal that when there is an improvement in the information environment after the punctuation by an economically significant fundamental shock - the Non-Tradable Share (NTS) reform in China in April 2005 - technical analysis work better post-NTS reform during 2005-09 for stocks with *higher* R^2 , consistent with the *Price-Informativeness Hypothesis*, and generally for *older* and bigger stocks with lower turnover and higher market-to-book ratio. Thus, without the guide of R^2 , investors should take the market prognosis by all these “alchemists” with their “voodoo” charts with a heavy dose of salt. We also reconciled the lively debate and extremely mixed evidence on the *interpretation* of R^2 and its relationship with the cross-sectional returns of stocks.

The rest of the paper is organized as follows. Section 2 explores the literature review and hypotheses development. Section 3 describes the data, variable description and construction, and methodology. Section 4 presents the empirical results, while Section 5 examines the robustness of the results in sub-periods. Section 6 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Technical Trading Rules

Two empirical papers were particularly important in supporting the predictive capabilities of technical trading rules. Brock, Lakonishok and LeBaron (BLL, 1992) found significant technical trading profits by utilizing 26 trading rules to a very long data series of the Dow Jones index daily prices from 1897 to 1986. Lo, Mamaysky and Wang (2000) used a non-parametric kernel regression pattern recognition method to automate the evaluation of technical analysis trading techniques over the period from 1962 to 1996, and found strong evidence that there is incremental informational and practical value in technical analysis, particularly in NASDAQ stocks.

BLL (1992) results remain robust even after correcting for the leptokurtic, conditionally heteroskedastic, autocorrelated, and time-varying distribution in stock returns using the model-based bootstrap technique to overcome the weaknesses of conventional t-tests. However, Sullivan, Timmerman and White (STW, 1999) pointed out in that data-snooping biases can be severe when evaluating technical rules, which can lead to the false conclusion that technical trading strategies can predict future price movements. In particular, STW (1999) repeated BLL (1992) study by utilizing White’s (2000) Reality Check bootstrap methodology to correct for data-snooping biases and find that the trading rules examined do not generate superior out-of-sample performance. BLL acknowledged that possible data snooping biases remain when they use a range of rules chosen *ex post*. They argue that such dangers are minimized by the deliberate choice of a simple class of rules that has been in common use for a long period of time. Interestingly, STW acknowledged that they found BLL in-sample results to be robust to data-snooping over the 100-year period in BLL (1992).

However, our study is more concerned about investigating the source of the returns from the technical trading rules by testing its association with stock return synchronicity, rather than focusing on establishing the highly contentious point of whether the technical trading rules are indeed profitable and robust to problems such as data-snooping biases (Sullivan, Timmerman and White, 1999), since we acknowledge that these trading rules might perhaps *not* work for *certain* stocks at the firm-level, and we want to know what are the predictors that determine the trading profits or losses from applying these technical rules.

There are surprisingly few papers that examine the value of technical analysis in China. Chen and Li (2006) found weak evidence for technical trading profits over the period from 1994 to 2002, but only for 39 companies which cover “23 percent of the daily turnover of the entire A-share market”. There are some supporting evidence that technical analysis add value in emerging markets (Bessembinder and Chan, 1995; Ito, 1999), but Ratner and Leal (1999) found the opposite results after correcting for data-snooping bias and adjusting for round-trip transaction costs, while Chen, Huang and Lai (2009) found there is a sharp decline in trading profits after implementing a one-day lag scheme to account for non-synchronous trading bias in eight Asian markets. These studies exclude China in their analysis.

Given the extraordinary growth in China to become the world’s third largest stock market in recent years which were not in the sample period of most prior studies, it should be interesting to fill the gap in the extant literature findings by examining the source of returns predictability from deploying technical trading rules in a highly synchronous but fast-changing market like China.

2.2 R² or Stock Return Synchronicity

The dominant *interpretation* of R², or stock return synchronicity, is an important issue because prior research suggests that *more* informative stock prices, measured by *lower* R², lead to better resource allocation, and therefore functional efficiency with efficient stock prices directing capital to the highest-value users, which has implications for economic growth (Tobin, 1982; Wurgler, 2000; Durnev, Morck, and Yeung, 2004, Wang, Wu and Yang, 2009).

Since the influential studies by MYY (2000) and CLMX (2001) documenting the trend of lower R² over time, many proposed explanations have been instrumental in supporting the *Price Informativeness* story, that is, low R² is a reasonable measure for the quality of the information environment at either the country-level or the firm-level.

In particular, at the country-level, MYY find that stock prices are more synchronous (i.e. have higher R²) in emerging markets which are low-income countries with weak protection of investors’ and property rights; weak institutions discourage the acquisition of information about individual stocks and such markets lack informed traders because risk arbitrageurs find it more costly to keep their profits in such economies. At the firm-level, Durnev, Morck, Yeung and Zarowin (2003) find evidence that firm with lower R² exhibit higher associations between current returns and future earnings, suggesting that lower R² is indicative of better informationally-efficient prices. Piotroski and

Roulstone (2004) find that stocks with higher institutional trading and insider trading have lower R^2 . There is also evidence that Increased institutional ownership (Bennett, Sias, and Starks, 2003; Xu and Malkiel, 2003) is associated with lower R^2 . The idea is that Institutional trading contributes to private information collection and accelerates the incorporation of firm-specific information into stock prices (Hartzell and Starks, 2003), and provides a better explanation for a lower R^2 . Hutton, Marcus and Tehranian (2010) find that R^2 decreases with information transparency. Ferreira and Laux (2007) show that firms with better corporate governance (as measured by having fewer anti-takeover provisions) display higher trading activity, better information about future earnings in stock prices, and lower R^2 . Irvine and Pontiff (2009) found that lower R^2 could be due to product markets becoming more competitive.

In a widely-cited paper, Ang, Hodrick, Xing, and Zhang (2006) report that stocks with low R^2 (or high idiosyncratic volatility) is associated with “abysmally low returns”. The average differential between quintile value-weighted portfolios of the lowest and highest idiosyncratic volatility is about - 1.06 percent per month. Ang (2009) also confirm that the link also exists in 23 other developed markets. Jiang, Xu and Yao (2009) find that firms with past low R^2 (or high idiosyncratic volatility) tend to have more negative future unexpected earnings surprises, leading to their low future returns. There is overwhelming support for the *Price Informativeness* story of R^2 .

The *Noise Hypothesis* is originated by Shiller (1981) who finds that the level of stock price volatility is too high to be explained by the volatility in the underlying fundamentals, e.g. dividends. West (1988) provides a theoretical model in which low R^2 is associated with less firm-specific information and more noise in returns. In West’s model, relatively more information results in prices being closer to fundamental values, and the release of new information results in smaller price movements and lower R^2 . West empirically tests his model and reports results indicating that lower R^2 is positively associated with bubbles, fad, and other non-fundamental factors. Recent evidence by Brandt, Brav, Graham and Kumar (2010) show that the trend of lower R^2 is a speculative episodic event driven by low-priced stocks dominated by retail traders and that there is a reversal to higher R^2 (or lower idiosyncratic firm volatility) during the 2000s, using small trades data from ISSM/TAQ and brokerage data. Other direct or implicit opposing explanations of the *Price Informativeness* story view include firm fundamentals become more volatile, such as an increase in the variance of return on equity (Wei and Zhang 2006) or opaqueness in financial accounting information (Rajgopal and Venkatachalam 2006); newly listed firms becoming increasingly younger (Fink et al. 2009) and riskier (Brown and Kapadia 2007).

Rebutting the widely-cited claims by Ang et al (2006), Fu (2009) reports that expected idiosyncratic volatility, estimated using the EGARCH model, is positively correlated with stock returns. Duffee (1995) found a positive contemporaneous relation between realized monthly idiosyncratic volatility and stock returns. Bali and Cakici (2008) show that the results in Ang et al (2006) are sensitive to the methodology used to form volatility portfolios and to the data frequency

used to estimate idiosyncratic volatility, and that the negative relationship between idiosyncratic volatility and expected returns disappears in the equal-weighted returns. Huang, Liu, Rhee and Zhang (2010) point out that the results in Ang et al (2006) may be driven by monthly return reversals.

Other studies supporting the *Noise Hypothesis* suggest that behavioural factors, bubbles, herding, and other non-fundamental factors affect stock return volatility (see Shleifer (2000) for a review), and ultimately the usefulness of the synchronicity measure as a gauge of firm-specific information. Behavioural models, like Barberis and Huang (2001) predict that lower R^2 stocks earn higher expected returns. In environments with frictions and incomplete information (Merton, 1987) and limits to arbitrage (Shleifer and Vishny, 1997), R^2 (or the idiosyncratic volatility of a stock) is linked to its expected return. Merton (1987) suggests that, in the presence of incomplete markets where investors have limited access to information, firm-specific risk cannot be fully diversified away, and thus firms with low R^2 require higher average returns to compensate investors for holding imperfectly diversified portfolios. In the influential “limits of arbitrage” argument by Shleifer and Vishny (1997), arbitrageurs tend to avoid stocks with low R^2 (or high idiosyncratic volatility) during the holding period, allowing these stocks to enjoy higher expected returns whose mispricing are not arbitrated away. These arbitrageurs care more about the short-run performance, because they use capital provided by investors, who tend to withdraw funds if the short-run performance is poor. Thus, they desire to keep the ratio of reward-to-risk over shorter horizons high and are less willing to take large positions in these stocks and thus the largest mispricing are found in these stocks which receive the least arbitrage resources.

In addition, Barberis, Shleifer and Wurgler (2005) also find significant changes in firms’ R^2 values surrounding additions and deletions to the S&P 500 Index in the U.S., consistent with market frictions influencing synchronicity. Since additions and deletions to indices do not signal new information to the market regarding firms’ fundamentals, the changes in firm’s R^2 values surrounding changes in the composition of indices is inconsistent with an information-based explanation of the R^2 measure. Consistent with the noise-in-returns interpretation of the R^2 measure, Kumar and Lee (2006) find that noise traders (uninformed retail investors) have a significant influence on stock price synchronicity. Thus, the findings of Barberis et al. (2005) and Kumar and Lee (2006) indicate that market frictions, i.e., factors unrelated to information, have a significant influence on stock price synchronicity. Other research supporting the *Noise Hypothesis* include Ali, Hwang and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006) and Zhang (2006).

2.3 Hypotheses

We posit that the source of the profitability (or losses) of technical trading rules could be due to varying degrees of firm-level synchronicity with the market, a relationship that has not been explored in prior literature. Yet, in the *cross-sectional* relationship between technical trading profitability and stock return synchronicity, the direction is *unclear* due to the two competing hypotheses, namely *Price Informativeness Hypothesis* and *Noise Hypothesis*. Given that China

appears to be a “noisy” market, we posit that there is a positive relationship in the regression of technical trading returns on ψ_i , which is the *inverse* measure of R^2 or *lack* of stock return synchronicity (we will explain the rationale for transforming the variable in Section 3.2), that is, a higher ψ_i or lack of stock return synchronicity (or *lower* R^2) is associated with *higher* technical trading returns. In other words, the coefficient on the synchronicity measure ψ_i is positively significant.

Our paper is similar in spirit to Teoh, Yang and Zhang (TYZ, 2009) and Chang and Luo (2010) who find *bigger* anomalies among *lower* R^2 stocks. The presence of anomalies indicates that stock prices are inefficient with respect to information about future cashflows that are contained in the predictive variables explored by TYZ (2009)². Their findings suggest that stocks whose returns have low R^2 may incorporate less information about future fundamentals, and are more difficult for investors to analyze accurately. Using a much larger sample size and different methodology compared to Durnev et al (2003), TYZ (2009) also find that firms with lower R^2 have smaller future earnings response coefficients (ERCs), indicating that their current stock price incorporates a smaller amount of future earnings news, and thus more uncertainty about future earnings news remains unresolved, which is inconsistent with Durnev et al (2003). In addition, low R^2 firms have worse information environment as measured by earnings quality, earnings persistence, and earnings predictability, and have higher probability of distress. These results imply that low R^2 stocks incorporate less information about future cashflows and thus *inconsistent* with the *Price-Informativeness Hypothesis* and more consistent with the *Noise Hypothesis*.

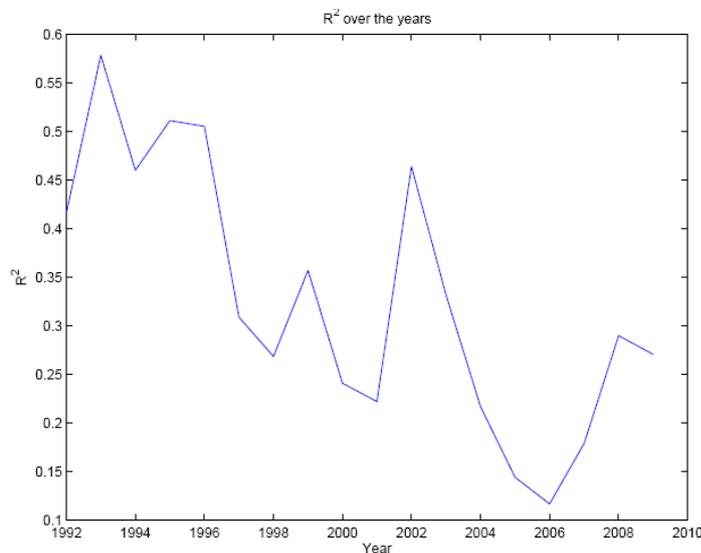


Figure 1: The declining synchronicity of China stock prices, or the declining fraction of China stock return variation explained by the market as measured by R^2 , the statistic from running a market model regression using weekly returns including dividend income from 1991 to 2009, using our sample size of 740 companies which represents around 90% of the population of stocks on Shanghai Stock Exchange in terms of market capitalization. Returns and indexes data are from Datastream. Note that the R^2 in MYY (2000) for China in 1995 was 45.3% reported in their Panel C of Table 2 which is consistent with MYY.

² They are (1) the post-earnings announcement drift or PEAD (Ball and Brown, 1968; Bernard and Thomas, 1990); (2) Value/Price or V/P (Lee, Myers and Swaminathan, 1998); (3) accruals (Sloan, 1996); and (4) net operating assets (Hirshleifer, Teoh and Zhang, 2004).

Figure 1 graphs the average R^2 across stocks, based on weekly returns from 1991 to 2009. We observe an overall declining trend in R^2 . This brought us to the attention on whether there are any time-series dynamics that could possibly affect the cross-sectional relationship between stock return synchronicity and technical trading returns. We examine this issue further in Section 4.

We like to emphasize that we do *not* explore the time-series dynamics on *why* R^2 is declining over time; rather, we are more interested in *what* this time-series trend for our main predictor in the synchronicity measure implies for the *direction* of the cross-sectional relationship between stock return synchronicity and technical trading returns. Specifically, we want to find out whether or not there is a *structural break* in the beta coefficient for the synchronicity measure ψ_i . If so, it will be unclear whether the relationship of higher returns from lower R^2 stocks still holds.

But what sub-period(s) should we investigate to assess whether our results are robust? To avoid data-snooping biases (Lo and MacKinlay, 1990), we ask if there are any economically significant fundamental shocks to the information environment faced by stocks in China over the period. Indeed, there is the important Non-Tradable Share (NTS) reform that was announced in April 2005. Following the NTS reform in 2005, the market capitalization of Shanghai Stock Exchange grew tremendously from around \$380 billion to around \$3 trillion at the end of 2009. Average R^2 from Jan 1991 to April 2005 in the pre-NTS reform period was 37 percent as compared to 21 percent in the post-NTS reform period from May 2005 to December 2009.

We hypothesize that the informational environment in China should improve in the post-NTS reform period during May 2005-09 to the extent that R^2 is now a measure that is more consistent with the *Price-Informativeness Hypothesis*. In other words, the NTS reform will lead to greater transparency for stocks and the cost-benefit trade-off on private information collection is improved, leading to more extensive informed trading and more informative pricing, as in the spirit of Grossman and Stiglitz (1980). Traders acquire more information about stocks and their prices are more volatile (equivalently, lower R^2) and more informative than the prices of stocks with more costly information. Thus the positive coefficient on the synchronicity measure ψ_i for the *overall* period from 1991-2009 should flip to the *negative* sign during the post-NTS sub-period. As a result, we hypothesize that low R^2 stocks will now have *lower* returns from the technical trading rules (*not* higher as were under the *Noise Hypothesis*) after the NTS reform where there is an economically significant fundamental shock to the information environment.

3. DATA, VARIABLE DESCRIPTION AND CONSTRUCTION, AND RESEARCH METHODOLOGY

We draw the data for our study from the *Datastream* database. Our initial sample includes all 847 firms traded on the Shanghai Composite Index since the inception of the Shanghai Stock Exchange from 2 Jan 1991 to 31 December 2009. After removing firms with more than 100 days of zero returns in any year in the construction of our returns from technical trading rules, requiring firms to have a minimum of 40 weeks of non-zero returns to estimate our synchronicity measure ψ_i , and that

the sample to contain data for the control variables which include *Market-to-Book*, *Size*, *Leverage*, *Dividend Payout* ratio, *Turnover*, and *Firm Age*, we are left with a final sample of 740 firms that represent, on average, 90 percent of the initial population of stocks in terms of market capitalization.

3.1 Technical Trading Rules

Following BLL (1992), we evaluate three types of rules: Variable Length Moving Average (VMA) rules, Fixed Length Moving Average (FMA) rules, and Trading Range Break (TRB) rules (resistance and support levels). BLL (1992) provide additional description and motivation for these trading rules, as well as some historical perspective on their usage:

- (a) *Variable Length Moving Average (VMA) and Fixed Moving Average (FMA)*: Moving average trading models take advantage of positive serial correlation in equity returns. A trading signal usually follows a large movement in stock price under the assumption that the autocorrelation bias in the time series trend will continue in the same direction. The VMA rules analyzed are as follows: 1 ± 50 , 1 ± 150 , 1 ± 200 , where the 1 represents the number of days in the short moving average, and the 50, 150 and 200 represent the number of days in the long moving average. Buy (sell) signals are emitted when the short-term average exceeds (is less than) the long-term average by at least a pre-specified percentage band (0 percent or 1 percent). This test is repeated daily with the changing moving averages throughout the sample. The buy position is a long position in the stock and is maintained until a sell signal is indicated. With the sell signal, the investor is out of the market. A rule is effective if the average buy minus sell (buy-sell) signal is positive, significant, and greater than a buy and hold alternative after trading costs. BLL (1992) evaluate each rule with a trading band of zero and one percent of returns. A zero band classifies each return to emit either a buy or sell signal, while a band of one would emit a buy or sell signal only when the short moving average crosses the trading band. With a band of zero, this method classifies all days into either buys or sells. Buy (sell) signals are emitted when the short moving average cuts the long moving average from below (above) and moves beyond it by the pre-specified band. Once a signal is emitted, VMA rules call for the position to be maintained until the short and long moving averages cross again, while FMA rules hold the position for a fixed number of days. We evaluate FMA strategies with fixed holding periods of ten days.
- (b) *Trading Range Break (TRB)*: TRB rules involve comparing the current price to the recent minimum and maximum. TRB rules emit buy signals when the current price exceeds the recent maximum by at least a pre-specified band, and emit sell signals when the current price falls below the recent minimum by at least the pre-specified band. The rationale for this rule is that when the current price reaches the previous peak, a great deal of selling pressure arises because many people would like to sell at the peak. However, if the price exceeds the previous peak, it is indicated that the upward trend has been initiated. Like BLL (1992), we evaluate separate TRB rules where recent minimums and maximums are defined as the

extreme observations recorded over the prior 50, 150, and 200 days, respectively. We use bands of 0 and 1 percent, making for a total of six TRB combinations, and then evaluate each TRB rule using fixed investment horizons of 10 days.

3.2 Synchronicity Measure ψ_i

MYY (2000) is the first in a series of papers that uses the R^2 of a regression of individual stock returns on the market return as a measure of synchronicity, or the extent to which the stock prices of individual firms within a country move together. R^2 is also the ratio of idiosyncratic volatility to systematic volatility; idiosyncratic volatility is thus the *inverse* measure of synchronicity. Thus, lower R^2 , or higher idiosyncratic volatility of individual firms, indicates lower synchronicity of stock returns. Following MYY (2000), we estimate firm-specific return variation using a two-factor international model which includes both the local and U.S. market index returns:

$$r_{it} = \alpha_i + \beta_1 r_{mt} + \beta_2 r_{ust} + e_{it} \quad (1)$$

using weekly return data; where r_{it} is the return of stock i in period t ; r_{mt} is the value-weighted local market return; and r_{ust} is the value-weighted U.S. market return.

Like MYY (2000) and other international studies, we use weekly returns to deal with infrequent trading in international markets. Following Dasgupta et al (2010), we compute the stock's *lack of synchronicity* as the ratio of idiosyncratic volatility to total volatility $\sigma_{ie}^2 = \sigma_i^2$ that is precisely $1 - R_i^2$ of Eq. (1). Given the bounded nature of R^2 ; we conduct our tests using a logistic transformation of $1 - R_i^2$:

$$\psi_i = \log(1 - R_i^2) \quad (2)$$

Thus, our predictor variable ψ_i measures idiosyncratic volatility relative to market-wide variation, or the *lack of synchronicity* with the market. One reason for scaling idiosyncratic volatility by the total variation in returns is that firms in some industries are more subject to economy-wide shocks than others, and firm-specific events may be correspondingly more intense. Additionally, this scaling and transformation allow for comparability to other studies. We do not add control variables to our price regression in (1) because MYY (2000) view the R^2 as a summary measure of the amount of information reflected in returns.

3.3 Relationship between Stock Return Synchronicity and Returns from Technical Trading Rules

We examine the relationship between technical trading returns and stock return synchronicity R^2 by estimating the following basic model:

$$TTR_i = \alpha + \beta \psi_i + \gamma \text{Firm Controls}_i + \varepsilon_i \quad (3)$$

where TTR_i is Technical Trading Returns calculated using the methodology by BLL (1992) discussed in section 2.1; the synchronicity measure ψ_i is estimated from a market model that was discussed in section 2.2; Firm Controls include those commonly used in the literature, namely, *Size* (defined as the logarithmic of market value); *Leverage* (net debt over book equity); *Dividend Payout* ratio (dividend over net profits); *Turnover* (annual volume over number of shares outstanding); *Firm Age* (the

number of years the company first appears on the Shanghai Exchange). We control for turnover as volume may provide relevant information if prices do not react immediately to new information (Blume, Easley and O’Hara, 1994).

The *Price-Informativeness Hypothesis* supports the view that expected returns from the predictor variable would be low; thus, the beta coefficient on the synchronicity measure ψ_i will be *negative*, that is, a *higher* ψ_i (*lower* R^2) is associated with *lower* returns from the technical trading rules. On the other hand, a *positive* beta coefficient on ψ_i is consistent with the *Noise Hypothesis*, that is, a *lower* R^2 is associated with *higher* returns.

4. EMPIRICAL RESULTS

4.1 Summary Statistics of Sample Characteristics and Returns from Technical Trading Rules

The summary statistics of R^2 , other sample characteristics and the average return from the three technical trading rules are reported in Panel A of Table 1. The average R^2 is 25 percent, which is a significant decline from the 45 percent reported in MYY (2000). Panel B of Table 1 reports the cross-sectional average of the correlation among the sample characteristics; most of the sample characteristics do not appear to be highly correlated with our main synchronicity predictor ψ_i .

The average annualized mean buy returns from the three technical trading rules are reported in Panel C of Table 1. Because China does not allow for short-selling of stocks, we report only the mean buy returns generated from the buy signal in the technical trading rules. They range from 22-42 percent (22-24 percent for VMA, 17-24 percent for FMA, and 22-47 percent for TRB), which is significantly higher than the unconditional annualized average return of 8 percent, and also higher than the 12 percent reported by BLL (1992) for U.S. Dow Jones index.

Table 1: Summary Statistics

Panel A presents the summary statistics of the sample characteristics. The construction details are described in Section 2. Panel B reports the cross-sectional average of the correlation among the sample characteristics. Results in Panel C are for daily data from January 1991 to December 2009 where mean buy returns using technical trading rules are annualized. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. Because China does not allow for short-selling of stocks, we report only the mean buy returns generated from the buy signal in the technical trading rules. Note that the unconditional annualized average return is 8%.

Panel A: Summary Statistics

	Mean	Median	Min	Max	Std
Synchronicity	0.25	0.25	0.06	0.51	0.06
Market-to-Book	3.89	3.24	-22.94	61.38	3.30
Size	1.70	0.27	0.06	261.16	11.96
Turnover	0.96	0.60	0.13	41.75	2.00
Leverage	0.34	0.24	-10.01	12.59	0.99
Dividend Payout	24.37	22.44	0.00	78.18	17.14
Firm Age	9.80	9.00	1.00	19.00	3.90
Annual Return	0.08	0.07	-0.53	0.57	0.10
Return(VMA(150,1,0))	0.22	0.20	-0.98	1.10	0.22
Return(FMA(150,1,0,10))	0.22	0.20	-1.43	1.06	0.22
Return(TRB(150,0,10))	0.42	0.37	-2.23	3.52	0.63

Panel B: Pearson Correlations

	Synchronicity	Market-to-Book	Size	Turnover	Leverage	Dividend Payout	Firm Age
Synchronicity	1	-0.08	0.27	0.19	-0.02	0.16	0.18
Market-to-Book		1	-0.01	0.13	0.12	-0.19	0.13
Size			1	0.05	-0.05	0.08	-0.19
Turnover				1	-0.09	0.06	-0.05
Leverage					1	-0.16	0.10
Dividend Payout						1	-0.10
Firm Age							1

Panel C: Results for the Technical Trading Rules (VMA, FMA and TRB)

Period	Rule	Type	Mean	Std
1992-2009	VMA	(1,50,0)	0.24	0.20
		(1,50,0,01)	0.25	0.21
		(1,150,0)	0.22	0.22
		(1,150,0,01)	0.22	0.23
		(1,200,0)	0.22	0.22
		(1,200,0,01)	0.23	0.23
	FMA	(1,50,0,10)	0.17	0.19
		(1,50,0,01,10)	0.19	0.20
		(1,150,0,10)	0.22	0.22
		(1,150,0,01,10)	0.22	0.22
		(1,200,0,10)	0.23	0.21
		(1,200,0,01,10)	0.24	0.22
	TRB	(50,0,10)	0.32	0.41
		(50,0,01,10)	0.32	0.44
		(150,0,10)	0.42	0.63
		(150,0,01,10)	0.41	0.66
		(200,0,10)	0.47	0.69
		(200,0,01,10)	0.46	0.76

4.2 Properties of R^2 Deciles and Univariate Analysis

From Table 2, we find that low R^2 stocks are generally smaller, younger, have a lower dividend payout ratio, and a higher leverage ratio. According to Baker and Wurgler (2006), such stocks are more difficult to value and their prices tend to be affected by investor sentiment, and they are more difficult to arbitrage, which could potentially result in these stocks having higher expected returns to compensate investors as argued earlier in the “limits of arbitrage” insight proposed by Shleifer and Vishny (1997) and consistent with the *Noise Hypothesis*. Interestingly, there is not any significant difference between the lowest decile R^2 stocks and the highest ones in the market-to-book ratio. Also, high R^2 stocks have a higher turnover ratio.

In addition, returns from technical trading rules have a *negative* association with stock return synchronicity, or the R^2 . Thus, we find evidence in favor of the *Noise Hypothesis* in that stocks with *lower* R^2 earn *higher* profits from technical trading rules. Sorting the sample by R^2 into deciles of 10 portfolios, we find that the technical trading returns in N1 (lowest R^2 portfolio) exceeds that in N10 (highest R^2 portfolio) by an annualized 10-37 percent over the sample period, depending on the type of technical trading rule that is employed. In particular, the spread differential between the highest and lowest R^2 portfolios is the highest for the TRB technical trading rule.

In the next section, we carry out a multivariate regression analysis of equation (3) outlined in Section 2.3 to control for the firm-level characteristics (market-to-book, size, leverage, dividend

payout ratio, turnover, and firm age) in order to ensure that our findings of the negative relationship between technical trading returns and stock return synchronicity are robust.

Table 2: Characteristics of R² Portfolios

Stocks are sorted into deciles of 10 portfolios based on the level of their average R² over the sample period from low (L) to high (H).

	N1(L)	N2	N3	N4	N5	N6	N7	N8	N9	N10(H)	N10-N1	t(N10-N1)
Synchronicity	0.16	0.19	0.21	0.22	0.24	0.25	0.27	0.29	0.32	0.38	0.22	4.40
Market-to-Book	4.04	3.64	4.46	3.91	5.19	3.89	3.59	3.34	3.41	3.41	-0.62	-0.72
Size	0.31	0.31	0.44	0.42	0.52	0.55	0.61	0.55	2.30	10.92	10.62	2.23
Turnover	0.61	0.65	0.74	0.83	0.76	0.81	0.96	0.97	1.63	1.64	1.03	3.56
Leverage	0.14	0.29	0.43	0.53	0.34	0.22	0.27	0.35	0.37	0.46	0.32	3.45
Dividend Payout	18.09	20.40	21.04	20.34	24.77	23.57	23.23	28.25	26.40	28.27	10.19	1.25
Firm Age	8.43	8.79	9.47	9.73	9.65	9.87	10.62	10.50	10.90	11.54	3.11	4.23
Annual Return	0.09	0.07	0.04	0.05	0.11	0.11	0.07	0.09	0.09	0.04	-0.05	-0.78
Return(VMA(150,1,0))	0.29	0.26	0.25	0.24	0.23	0.21	0.19	0.19	0.19	0.19	-0.10	-4.32
Return(FMA(150,1,0,10))	0.29	0.25	0.26	0.24	0.22	0.22	0.19	0.21	0.19	0.18	-0.11	-3.98
Return(TRB(150,0,10))	0.63	0.54	0.50	0.42	0.45	0.44	0.25	0.25	0.26	0.26	-0.37	-2.95

4.3 Multivariate Regression

The multivariate analysis of the regression model from Section 2.3 to investigate the relationship between technical trading returns and synchronicity is presented in Table 3. The coefficient on the synchronicity measure ψ_i remains positive and significant after controlling for a battery of firm-level characteristics that include *Market-to-Book*, *Size*, *Turnover*, *Leverage*, *Dividend Payout* and *Firm Age* across all three technical trading rules. Thus, the findings are consistent with the *Noise Hypothesis* in that stocks with higher ψ_i (lower R²) have higher technical trading returns.

In addition, we find that the coefficients on the fundamental-based factors i.e. *Market-to-Book*, *Leverage* and *Dividend Payout*, are insignificant across all three technical trading rules. This is an appealing and intuitive result in that we should not expect any relationship between these fundamental factors and technical trading returns since technical trading rules rely on non-fundamental trading signals.

Finally, we find that *Firm Age* and *Turnover* are significantly negatively related to technical trading returns, whereas Firm Size is significantly positively associated with technical trading returns, across all three technical trading rules. Thus, *larger* and *younger* stocks with *lower* turnover have *higher* technical trading returns. If turnover is a proxy for liquidity as suggested by existing literature, the result is consistent since investors may demand a liquidity premium for low liquidity stocks which are more costly to trade. Dasgupta et al (2010) find that younger firms tend to have significantly lower R² than do older firms, since the new information content (surprise) is larger for younger firms (Dubinsky and Johanness, 2006) and that would drive higher firm-specific return variation. Thus, their results suggest that younger firms have higher returns according to the *Noise Hypothesis*. However, the findings that larger stocks have higher technical trading returns is a counter-intuitive and important result because of the well-known “size effect” documented by Black (1976) and Banz (1981) in that smaller firms have higher risk-adjusted returns, on average, than larger firms. Marshall,

Qian and Young (2009) also found that technical analysis is more profitable for smaller stocks, albeit in U.S. over 1990-2004. We leave this interesting puzzle for future research.

Table 3: Relationship between Technical Trading Returns and Synchronicity (1992-2009)

This table reports the relationship between technical trading returns and synchronicity in the following model:

$$TTR_i = \alpha + \beta \psi_i + \gamma \text{Firm Controls}_i + \varepsilon_i$$

where the dependent variable TTR_i is Technical Trading Returns calculated using the methodology by BLL (1992) discussed in section 2.1; the synchronicity measure ψ_i is estimated from a market model that was discussed in section 2.2; *Firm Controls* include those commonly used in the literature, namely, *Size* (defined as the logarithmic of market value); *Leverage* (net debt over book equity); *Dividend Payout* ratio (dividend over net profits); *Turnover* (annual volume over number of shares outstanding); *Firm Age* (the number of years the company first appears on the Shanghai Exchange). Panel A, B, and C regress technical trading returns from applying the VMA, FMA and TRB rule on the synchronicity measure and firm controls respectively. Model (1) regresses technical trading returns on only the synchronicity measure ψ_i . Model (2) includes the additional control variables *Market-to-Book* and *Size*. Model (3) includes the rest of the control variables, namely *Turnover*, *Leverage*, *Dividend Payout* and *Firm Age*. The numbers in parentheses are t-ratios based on Newey-West standard errors.

	Panel A: VMA (1, 150, 0)			Panel B: FMA (1, 150, 0, 10)			Panel C: TRB (150, 0, 10)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.29 (10.12)	0.08 (1.29)	0.16 (2.36)	0.25 (9.09)	0.06 (0.10)	0.10 (1.47)	0.61 (7.67)	-0.20 (-1.19)	0.22 (1.10)
Synchronicity	0.22 (2.39)	0.42 (4.10)	0.12 (3.21)	0.11 (1.26)	0.30 (3.04)	0.04 (2.45)	0.65 (2.50)	1.30 (4.58)	0.75 (2.51)
Market-to-Book	- (-)	-0.002 (-0.72)	0.004 (1.58)	- (-)	-0.003 (-1.07)	0.003 (1.50)	- (-)	0.009 (1.31)	0.01 (1.58)
Size	- (-)	0.03 (4.22)	0.03 (3.79)	- (-)	0.03 (4.09)	0.04 (3.31)	- (-)	0.12 (5.35)	0.09 (3.72)
Turnover	- (-)	- (-)	-0.04 (-8.60)	- (-)	- (-)	-0.04 (-10.65)	- (-)	- (-)	-0.02 (-2.26)
Leverage	- (-)	- (-)	-0.002 (-0.28)	- (-)	- (-)	0.006 (0.79)	- (-)	- (-)	0.017 (0.77)
Dividend Payout	- (-)	- (-)	-0.0003 (-0.66)	- (-)	- (-)	-0.0001 (-0.17)	- (-)	- (-)	-0.003 (-2.90)
Firm Age	- (-)	- (-)	-0.02 (-6.95)	- (-)	- (-)	-0.01 (-6.94)	- (-)	- (-)	-0.03 (-4.84)
Adj. R^2	0.006	0.0282	0.165	0.0008	0.0223	0.199	0.007	0.0223	0.08

5. SUB-PERIOD ANALYSIS AND THE NON-TRADABLE SHARE (NTS) REFORM IN 2005

Following the Non-Tradable Share (NTS) reform that was announced in April 2005, the market capitalization of Shanghai Stock Exchange grew tremendously from around \$380 billion to around \$3 trillion at the end of 2009. Average R^2 from Jan 1991 to April 2005 in the pre-NTS reform period was 37 percent as compared to 21 percent in the post-NTS reform period from May 2005 to December 2009.

We hypothesize that the informational environment in China should improve in the post-NTS reform period during May 2005-09 to the extent that R^2 is now a measure that is more consistent with the *Price-Informativeness Hypothesis*. In other words, the NTS reform will lead to greater transparency for stocks and the cost-benefit trade-off on private information collection is improved, leading to more extensive informed trading and more informative pricing, as in the spirit of Grossman and Stiglitz (1980). Traders acquire more information about stocks and their prices are more volatile (equivalently, lower R^2) and more informative than the prices of stocks with more costly information. Thus the positive coefficient on the synchronicity measure ψ_i for the *overall* period from 1991-2009 should flip to the *negative* sign during the post-NTS sub-period. As a result, we hypothesize that low

R^2 stocks will now have *lower* returns from the technical trading rules (*not* higher as were under the *Noise Hypothesis*) after the NTS reform where there is an economically significant fundamental shock to the information environment.

Section 5.1 covers some institutional background information on the NTS reform. Section 5.2 outlines the Chow Test to detect the presence of a structural break in beta coefficient for the synchronicity measure ψ_i . Section 5.3 details the empirical results of the relationship between technical trading returns and synchronicity in the two sub-periods, that is, pre-and post-NTS reform (1992-04/2005 and 5/2005-2009), and a discussion on the implications of the findings.

5.1 Institutional Background on the Non-Tradable Share (NTS) Reform

The Shanghai and Shenzhen Stock Exchanges were established in December 1990 and July 1991 respectively. Non-tradable shares (NTS) prior to the 2005 reform composed of legal-person shares and state shares are held by SOEs or government agencies. Legal-person shares were transferable between domestic institutions upon the approval of CSRC. Tradable shares composed of A-shares (denominated in local currency) and B-shares (denominated in foreign currencies and reserved for foreign investors, and H-shares³). The non-tradable portion was as high as 72 percent in 1993, and well over 60 percent prior to the NTS reform in 2005. According to the data from Chinese Security Regulatory Committee (CSRC), institutional investors held 28.89 percent of the value of tradable shares at the end of 2007, an increase by almost 25 percent compared to 2001. Before the NTS reform in 2005, the ownership structure in Chinese firms was concentrated, representing a partial transition from an economy in which most enterprises were owned by the state. At least 80 percent of the listed firms were created from the existing state-owned enterprises (SOEs) through carve-outs, in which the original business group remains as the parent firm, as well as the controlling shareholder. The largest shareholder controls more than 40 percent of the total shares in around 80 percent of listed firms, while the second largest shareholder typically owns less than 10 percent.

The conflicting incentives of controlling and minority shareholders caused by this split-share ownership structure can lead to significant inefficiencies inside the firm (Shleifer and Vishny, 1986, 1993; Rajan and Zingales, 2003). It has been argued that prior to the NTS reform, managers focused too much on book value, since any trades of state shares or legal shares approved by the CSRC took place at book value (Allen et al, 2007). Aharony, Lee and Wong (2000) documented that Chinese SOEs engage in financial packaging for public listing. Allen et al (2005) showed that China's formal sector (consisting of state-controlled firms) underperforms the "informal sector" of non-state-owned firms. Ball, Kothari and Robin (2000) provide evidence that accounting income in China lacks timely incorporation of economic loss because of political influence on financial reporting practices.

³ While the two share classes of A and B shares issued by the same firm are identical in terms of shareholder rights (e.g., voting and dividend), B shares were traded at a significant discount relative to A shares and are traded less frequently than A shares. The "B share discount" has been reduced significantly since the CSRC allowed Chinese citizens to trade B shares (with foreign currency accounts) in 2001. In addition, Class H shares, issued by selected "Red Chip" Chinese companies, are listed and traded on the HKSE.

Piotroski, Wong and Zhang (2009) find that state-controlled firms suppress negative financial information around visible political events. Since the blockholders could not sell their shares, they were inclined to expropriate wealth from minority shareholders (LaPorta et al, 2002; Wei, Xie and Zhang, 2005; Cao, Dybvig and Qiu, 2007; Cheung et al, 2009; Chen, Jian and Xu, 2009). There is also evidence of significant cash transfer or tunnelling of resources via related lending from listed firms back to controlling owners after related-party transactions (Jian and Wong, 2008). State shareholders are also less inclined to discipline their CEOs (Chang and Wong, 2009).

On 31 January 2004, the state council called for comments on how to promote the share-trading reforms. This showed the Chinese government's determination to change the structure of the stock market⁴. On 29 April 2005, under the permission of state council, the CSRC issued "Notice on the Pilot Reform of the Share-Trading Business of Listed Companies". Under the new plan, the remaining state shares among listed firms are converted to "G" shares and are tradable⁵. Four listed firms were in the pilot scheme that started the NTS reform process⁶. On 4 September 2005, CSRC issued *Administrative Measures on Non-tradable Share Reform in Listed Companies* and the reform had gone into real implementation from the pilot stage. By November 2006, 1,200 firms accounting for 96 percent of listed companies had completed the restructuring. By the end of 2007, there were only a few companies that have not reached an agreement with their shareholders on the terms of the reform.

During the reform, many new regulatory policies were launched, such as new accounting standards which aimed to improve transparency and to protect the interest of minority shareholders⁷.

5.2 Structural Break Analysis

In the last section, we find that model (3) has the highest adjusted R^2 for all three technical trading rules. We select model (3) to carry out our Chow Test to examine whether the coefficient on synchronicity is different in the two sub-periods, that is, pre-and post-NTS reform (1992-04/2005 and

⁴ From the latter half of 1998 to the first half of 1999, the Chinese government began an explorative trial to decrease state shares (known as *Guoyougu Jianchi*). The trial was stopped soon because of the big gap between expectation and market reactions. On 12 June 2001, the State Council of China issued *Provisional Measures on Reducing State Shares and Raising Social Security Funds*. On July 24, 2001, the government announced that it would sell some fraction of its remaining shares to ordinary investors, suddenly giving credibility and clarity to an ambiguously worded prior statement on future privatization (Calomiris et al, 2008). Again, considering the poor market reaction, the regulation was suspended on 22 October 2001 and cancelled on 23 June 2002.

⁵ The CSRC outlines the format for compensating existing shareholders and also imposes lockups and restrictions on the amount of G shares that can be sold immediately after they become tradable. More specifically, the new plan stipulates that G shares are not to be traded or transferred within 12 months after the implementation of the share structure reform. Shareholders owning more than 5% of the original non-tradable shares can only trade less than 5% of the total shares outstanding within one year and less than 10% within 2 years. These restrictions of G share sales are intended to reduce the downward pressure on the stock price, maintain market stability and protect the interests of public investors. The details of the "fully floating plan" for a firm, including the number of G shares to be granted to each Class A shareholder and the time window (e.g., one to three years) of G shares become fully floating, must be approved by two thirds of Class A shareholders of the firm.

⁶ The first batch of the four pilot companies is Tsinghua Tongfang, Hebei Jinniu Energy Resources, Shanghai Zijiang Enterprises Group and Sany Heavy Industry.

⁷ Other complementary policy measures must be undertaken before outside investors are willing to devote costly resources to the production of information. Ball (2001) argued that simply transporting rules from one economic environment to another can be unfruitful. Overall improvement in price informativeness is concentrated in countries with a strong macro infrastructure in terms of the efficiency of the judicial system, investor protection, and financial reporting.

5/2005-2009). We implement the three different trading rules (VMA (150,1,0), FMA (150,1,0,10), TRB (150,0,10)) in the two sub-periods to obtain the returns for our sample of stocks. The synchronicity measure ψ_i and the firm control factors for each sub-period are calculated using the same approach as outlined in the previous sections. Thus, we have:

$$TTR_{1i} = \alpha_1 + \beta_1 \psi_{1i} + \gamma_1 \text{Firm Control}_{1i} + \varepsilon_i \text{ where } i, i = 1, 2, \dots, n1$$

$$TTR_{2i} = \alpha_2 + \beta_2 \psi_{2i} + \gamma_2 \text{Firm Control}_{2i} + \varepsilon_i \text{ where } i, i = 1, 2, \dots, n2$$

and the corresponding null hypotheses:

$$H_0^1 : \alpha_1 = \alpha_2, \beta_1 = \beta_2, \gamma_1 = \gamma_2.$$

$$H_0^2 : \beta_1 = \beta_2.$$

Table 4: Probability Values for Tests of H_0^1 and H_0^2

	H_0^1	H_0^2
VMA	0.000	0.002
FMA	0.000	0.004
TRB	0.020	0.023

The probability values for these tests are given in Table 4 and we reject the null hypotheses that the coefficient on the synchronicity measure ψ_i is equal. Thus, there exists a structural break pre- and post-NTS reform (i.e. before and after 5/2005).

5.3 Empirical Results of the Relationship between Technical Trading Returns and Synchronicity Pre- and Post NTS Reform⁸

The average annualized mean buy returns from the three technical trading rules in the two sub-periods are reported in Table 5. The technical trading returns are negative during the pre-NTS reform sub-period, ranging from -4 to -33 percent depending on the technical rules applied, compared to the unconditional annualized average return of -15 percent. Post-NTS reform, the technical trading returns are hugely positive, ranging from 35 to 65 percent depending on the technical rules applied, which is better than the unconditional annualized average return of 25 percent.

Table 6 show the important result that the sign of the coefficient in the synchronicity measure ψ_i for the VMA and FMA technical rule flips from positive during the pre-NTS reform period and to negative during the post-NTS reform period as hypothesized. While the sign for the TRB rule remains positive, it has now become insignificant. In other words, lower R^2 stocks will now have *lower* returns from the technical trading rules (not higher as were under the *Noise Hypothesis*) after the NTS reform. When there is an economically significant fundamental shock to the information environment as was the case for the NTS reform, R^2 is now a proxy measure for informative prices and a measure that is more consistent with the *Price-Informativeness Hypothesis*.

⁸ The results are robust when the real policy implementation announcement on 4 September 2005 is used as the break date, rather than the 9 April 2005 pilot scheme announcement.

Table 5: Results for the Technical Trading Rules (VMA, FMA and TRB) Pre- and Post-NTS Reform

Results in Table 5 are for daily data for the two sub-periods: pre-NTS reform from 4/1992-2005 and post-NTS reform from 5.2005-2009. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. Because China does not allow for short-selling of stocks, we report only the mean buy returns generated from the buy signal in the technical trading rules. Note that the unconditional annualized average return is -15% pre-NTS reform and 25% post-NTS reform.

Rule	Type	Sub-period	Mean	Std	Sub-period	Mean	Std
VMA	(1,50,0)	1992-4/2005	-0.14	0.43	5/2005-2009	0.44	0.25
	(1,50,0.01)		-0.15	0.46		0.44	0.27
	(1,150,0)		-0.24	0.53		0.40	0.26
	(1,150,0.01)		-0.25	0.59		0.40	0.27
	(1,200,0)		-0.33	0.91		0.39	0.25
	(1,200,0.01)		-0.33	0.77		0.39	0.25
FMA	(1,50,0,10)		-0.14	0.36		0.35	0.25
	(1,50,0.01,10)		-0.14	0.37		0.36	0.26
	(1,150,0,10)		-0.21	0.42		0.40	0.26
	(1,150,0.01,10)		-0.21	0.43		0.40	0.27
	(1,200,0,10)		-0.24	0.59		0.39	0.24
	(1,200,0.01,10)		-0.25	0.61		0.40	0.25
TRB	(50,0,10)		-0.15	0.60		0.55	0.51
	(50,0.01,10)		-0.14	0.70		0.56	0.55
	(150,0,10)		-0.16	0.91		0.62	0.71
	(150,0.01,10)		-0.18	1.06		0.63	0.76
	(200,0,10)		-0.04	0.90		0.64	0.80
	(200,0.01,10)		-0.07	0.96		0.65	0.85

Table 6: Technical Trading Returns and Synchronicity Pre- and Post-NTS Reform

This table reports the relationship between technical trading returns and synchronicity in the following model:

$$TTR_i = \alpha + \beta \psi_i + \gamma \text{Firm Controls}_i + \varepsilon_i$$

where the dependent variable TTR_i is Technical Trading Returns calculated using the methodology by BLL (1992) discussed in section 2.1; the synchronicity measure ψ_i is estimated from a market model that was discussed in section 2.2; *Firm Controls* include those commonly used in the literature, namely, *Size* (defined as the logarithmic of market value); *Leverage* (net debt over book equity); *Dividend Payout* ratio (dividend over net profits); *Turnover* (annual volume over number of shares outstanding); *Firm Age* (the number of years the company first appears on the Shanghai Exchange). Panel A and B presents the results from the regression of technical trading returns from applying the VMA, FMA and TRB rule on the synchronicity measure and firm controls for the two sub-periods 1/1992-4/2005 and 5/2005-12/2009 respectively. The numbers in parentheses are t-ratios based on Newey-West standard errors.

Panel A: Pre-NTS Reform Sub-Period 1/1992-4/2005

	VMA	FMA	TRB
Intercept	-1.58 (-7.78)	-1.49 (-9.46)	-2.01 (-5.59)
Synchronicity	0.15 (2.84)	0.31 (2.14)	1.23 (3.77)
Market-to-Book	-0.004 (-0.62)	0.004 (0.77)	-0.029 (-1.79)
Size	0.09 (3.95)	0.10 (5.35)	0.27 (6.00)
Turnover	-0.02 (-2.77)	-0.03 (-3.60)	-0.10 (-2.63)
Leverage	0.006 (0.30)	0.007 (0.41)	0.009 (0.25)
Dividend Payout	0.0005 (0.38)	0.006 (0.62)	-0.006 (-2.97)
Firm Age	-0.06 (-8.99)	-0.053 (-10.38)	-0.045 (-3.93)
Adj. R^2	0.142	0.179	0.076

Panel B: Post-NTS Reform Sub-period 5/2005-12/2009

	VMA	FMA	TRB
Intercept	0.08 (0.98)	0.09 (1.14)	0.04 (0.15)
Synchronicity	-0.41 (-3.19)	-0.40 (-3.12)	0.19 (0.52)
Market-to-Book	0.006 (2.08)	0.005 (1.68)	0.02 (2.44)
Size	0.02 (1.83)	0.02 (1.83)	0.08 (2.74)
Turnover	-0.04 (-7.86)	-0.04 (-9.14)	-0.02 (-1.16)
Leverage	-0.008 (-0.83)	0.002 (0.25)	0.010 (0.41)
Dividend Payout	-0.001 (-1.89)	-0.001 (0.90)	-0.006 (-3.41)
Firm Age	0.01 (3.82)	0.01 (3.52)	0.03 (3.43)
Adj. R^2	0.094	0.113	0.052

The implications for these findings are important since it reconciles the lively debate and extremely mixed evidence on the *interpretation* of the synchronicity measure. Does low R^2 stand for informed trading leading to more informative prices under the *Price-Informativeness Hypothesis*, or does it imply noisy trading, limits of arbitrage or/and incomplete market under the *Noise Hypothesis*? As emphasized, these two competing hypotheses have starkly different relationship with expected returns, that is, both informed and noisy trading lead to low R^2 , but the former is related to lower expected returns, while the latter indicate higher expected returns.

Thus, technical trading rules work better for low R^2 stocks when the information environment does not experience any economically significant fundamental shock, such as the case for China during the sub-period from 1991 till April 2005 before the NTS reform, which is consistent with the *Noise Hypothesis*. However, an economically significant fundamental shock to the information environment will lead to the synchronicity measure to become a proxy for informative pricing, as was the case for China post-NTS reform from May 2005 till December 2009, resulting in lower technical trading returns to low R^2 stocks, consistent with the *Price-Informativeness Hypothesis*.

After an economically significant fundamental shock to the information environment, higher technical trading returns come from stocks with *higher* R^2 for the VMA and FMA technical rules, and generally for *older* (not younger) and bigger stocks with lower turnover. In addition, we observe that the coefficient on the fundamental factor *Market-to-Book* is now significantly positive. If MTB is a proxy for “growth” stocks (Lakonishok, Shleifer, and Vishny, 1994), the result indicates that these companies have higher technical trading returns. When MTB is a proxy for distress (Fama and French, 1993, 1995) and profitability⁹ (Daniel and Titman, 2006; Ecker, Francis, Olsson and Schipper, 2009), the result suggests that *less distressed* and *less profitable* stocks have *higher* technical trading returns.

To sum up, the relationship between stock return synchronicity and technical trading returns is negative over the period 1991-2009, that is, *low* R^2 stocks have *higher* technical trading returns, consistent with the Noise Hypothesis. Post-NTS reform, during the period from May 2005-2009, stock return synchronicity and technical trading returns are positively related, that is, *low* R^2 stocks have *lower* technical trading returns, consistent with the *Price-Informativeness Hypothesis*. We do not find this result to be conflicting. After all, we have only around *four* years of informed trading post-NTS reform during May 2005 to December 2009 as compared to around *fourteen* years of noise trading pre-NTS reform during January 1991 to April 2005, and the overall sample period from 1991-2009 is therefore dominated by noise trading, and hence the overall significantly negative relationship between stock return synchronicity and technical trading returns can be justified. As the information environment in China improves going forward in the next few decades, we can expect that the interpretation of R^2 to be more consistent with the *Price-Informativeness Hypothesis*.

⁹ Daniel and Titman (2006) dispute Fama and French’s (1995) analysis of the book-to-market ratio as an indicator of distress, and perform their own analysis of this ratio as an indicator of valuation-relevant information that is not contained in past accounting-based performance measures

Interestingly, the results suggest that fundamental analysis could play a bigger role in the gathering of relevant firm-specific information for decision-making in investing in developing transitional economies determined in establishing the institutional structures and complementary changes in country infrastructure to create incentives for higher quality informational environment and good governance to protect investors' rights.

A higher quality informational environment is important because the risk generated by noise trading can reduce the capital stock and consumption of the economy (De Long et al, 1989), and also forces managers to focus on the short term, and to bias the choice of investments against long-term projects. Shleifer and Summers (1990) argued that even if investors earn higher average returns from noise trading, it is because they bear more risk than they think. And even if they get rich over time, it is only because they underestimate the risk and get lucky.

There are policy implications in noise trading. Shleifer and Summers (1990) gave the analogy that making it costly for noise traders to bet on the stock market to protect them from their own utility losses is in principle identical to the case for prohibiting casinos, horse races, and state lotteries. In addition, noise trading benefit arbitrageurs who take advantage of noise traders. For instance, when noise traders are optimistic about particular securities, it pays arbitrageurs to create more of them. These securities might be mutual funds, new share issues, penny oil stocks, or junk bonds: anything that is overpriced at the moment. Just as entrepreneurs spend resources to build casinos to take advantage of gamblers, arbitrageurs build investment banks and brokerage firms to predict and feed noise trader demand. This suggests that regulatory actions could be needed when noise trading is prevalent to regulate the activities of these arbitrageurs taking advantage of the noise traders, as evident from the recent 2008 Financial Crisis with noise traders chasing subprime mortgage assets created by the financial institutions.

Thus, our results appear to suggest that the relationship between technical trading returns and R^2 can also help regulators to assess whether the informational environment is “noisy” or “informative”, and make their policy recommendations and regulatory actions accordingly.

6. SUMMARY AND CONCLUSION

We acknowledge that technical trading rules might perhaps *not* work for *certain* stocks at the firm-level, and we want to know about the *source* behind the trading profits or losses from applying these technical rules. We believe that we are the first to empirically establish the link between technical trading returns and stock return synchronicity. An additional and a very simple yet practical statistics - the R^2 - can guide trading decisions using technical trading rules¹⁰. Imagine that the Bloomberg terminal, Yahoo Finance and financial websites should have an additional statistics – the synchronicity measure – to allow investors and traders to assess how effective their technical analysis can be; for instance, if the informational environment is generally noisy, then the technical traders

¹⁰ Volatility is well-known to be persistent (Engle, 1982) and past idiosyncratic volatility, or R^2 , should still have predictive power when longer sample periods are used to compute R^2 .

should focus their efforts on less synchronous or low R^2 stocks to increase their probability of generating abnormal profits.

Do technical trading rules work? Possibly only when the R^2 is *low*, and for *larger* and *younger* stocks with *lower* turnover, consistent with the *Noise Hypothesis*. However, sub-period analysis reveal that when there is an improvement in the information environment after the punctuation by an economically significant fundamental shock - the NTS reform in China announced in April 2005 - higher technical trading returns post NTS-reform in 2005-2009 come from stocks with *higher* R^2 for the VMA and FMA technical rules, consistent with the *Price-Informativeness Hypothesis*, and generally for *older* (not younger) and bigger stocks with lower turnover and higher market-to-book (MTB). Thus, without the guide of R^2 , investors should take the market prognosis by all these “alchemists” with their “voodoo” charts with a heavy dose of salt¹¹. We thus reconcile the lively debate and extremely mixed evidence on the *interpretation* of R^2 and its relationship with the cross-sectional returns of stocks.

An economically significant fundamental shock to the information environment also lead to the significance of the *Market-to-Book* (MTB) ratio, suggesting that growth, distress and profitability (fundamental factors which MTB ratio proxies for) are important determinants to technical trading returns. Thus, fundamental analysis could play a bigger role in the gathering of relevant firm-specific information for decision-making in investing in developing transitional economies determined in establishing the institutional structures and complementary changes in country infrastructure to create incentives for higher quality informational environment and good governance to protect investors’ rights.

Our results also appear to suggest that the relationship between technical trading returns and R^2 can also help regulators to assess whether the informational environment is “noisy” or “informative”, and make their policy recommendations and regulatory actions accordingly. For instance, when the informational environment is noisy, regulatory actions could be needed to regulate the activities of arbitrageurs taking advantage of the noise traders to protect them from their own utility losses, as evident from the recent 2008 Financial Crisis with noise traders chasing subprime mortgage assets created by the financial institutions.

A cross-country study adapting our research methodology will likely be helpful to assess the relative usefulness and interpretation of R^2 .

Using a Bayesian framework, Treynor and Ferguson (1985) suggest that past prices, when combined with other valuable information, can be helpful in achieving unusual profit. He concludes that: “It is the non-price information that creates the opportunity. The past prices serve only to permit its efficient exploitation.” A natural important extension would be to examine the use of fundamental analysis in conjunction with technical analysis, which we leave for future research.

¹¹ The idea of scaling investment signals by the past idiosyncratic volatility of the stock is conveyed in a well-known book to practitioners, “Active Portfolio Management” (Grinold and Kahn 1999). Jacobs and Levy (1996) provide similar advice.

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