Essays on Stock Misvaluation

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ABSTRACT

This thesis consists of three essays on stock misvaluation in the Chinese stock market.

The Chinese stock market is dominated by risk-seeking speculators with behavioural biases. The first essay explores whether this leads to stock misvaluation and generates return premiums. We modify a pricing deviation-based approach developed by Rhodes–Kropf et al. (2005) by adding ownership classification in benchmark regressions to measure stock misvaluation, because one feature of many Chinese companies is state-ownership. We find that the accounting variables of the pricing deviation-based approach can explain more of the within-industry variation in firm value of state-owned enterprises (SOEs) than for non-state-owned enterprises (non-SOEs). The misvaluation effect of SOEs is stronger than non-SOEs, while the misvaluation of SOEs corrects faster than that of non-SOEs. Moreover, we find that loadings on the misvaluation factor positively forecast the cross-sectional returns in the rolling-window Fama-Macbeth two-stage regressions. The misvaluation effect in the Chinese stock market is significant.

The second essay examines the effect of market constraints on stock misvaluation. A pioneering study by Chang et al. (2014) demonstrates that intensified short-selling activities, not margin-trading activities, improve price efficiency after the ban on margin trading and short selling is lifted. We find that their finding is subject to the limitation of the short sample period and the result reverses after extending the sample period to December 2020, primarily due to the soaring margin-trading activities. The imbalanced development of margin trades and short sales positively affects stock misvaluation, escalating overvaluation while reducing undervaluation. The positive effect of the imbalanced trading activities on misvaluation is primarily sourced from margin trades. We argue that margin traders are information providers whose trading activities reduce undervaluation.

The third essay investigates the relationship between firm-level environmental, social and governance (ESG) score, and stock misvaluation. We find that the ESG score is negatively and significantly related to stock misvaluation. We extend our research by analysing the three pillars of ESG, as each pillar measures different aspects of a firm. The G score is negatively associated with stock misvaluation, effectively mitigating deviations from intrinsic value for overvalued and undervalued firms. The S score causes overvaluation, while the E score does not have a significant influence on misvaluation. These findings enhance the importance of evaluating E, S and G separately. The overall ESG score may counterbalance the influence of each individual ESG pillar on stock misvaluation. Further analyses show an influencing role of ESG (G) disclosure score in the ESG(G)- misvaluation relationship. The negative effect of the ESG (G) score on misvaluation is attributed to increasing information transparency.

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CHAPTER ONE

INTRODUCTION

This chapter presents an overview of the three essays included in this thesis. It outlines the gap in the literature that each essay aims to fill, the underlying motivations and contributions to the literature of this research. This chapter concludes by outlining the structure of the remainder of this thesis.

1.1. Overview of the Thesis

Asset pricing is a crucial dimension of the financial market. It plays a vital role in efficient capital allocation and in helping investors quantify the risk associated with different investment opinions by optimising risk-adjusted returns. However, assets are often not correctly valued on traditional risk factors, as behavioural biases, market frictions, etc., challenge the efficient market hypothesis (EMH). Hence, stock misvaluation emerges when stock prices are not correctly valued. This thesis aims to extend the literature on stock misvaluation.

This thesis is motivated by two prevalent themes in stock misvaluation literature. The first theme relates to the importance of the market environment. Investors have different trading patterns and behaviours in distinct market environments. The literature (Hirshleifer & Jiang, 2010; Chang et al., 2013) provides developed market evidence of the return predictive power of the misvaluation factor. China, as the world's second largest economy, exhibits unique investor composition and trading patterns compared with developed markets (Li & Wang, 2010; Ng & Wu, 2007; Peikun & Jing, 2010; Yu et al., 2019). The first essay of the thesis extends the knowledge on stock misvaluation and the associated risk premium in developing markets.

Furthermore, the second essay focuses on the effect of market constraints on stock misvaluation. Short-sale evidence from developed markets enhances the importance of lifting the short-sale ban (Miller, 1977; Diamond & Verrecchia,1987; Bris et al., 2007). In general, pioneers find that short-sale activities improve price efficiency by incorporating more negative views of investors into stock prices. In contrast, margin-trading evidence from the literature is controversial. On the one hand, margin traders amplify the noise trading (Chowdhry & Nanda, 1998; Rytchkov, 2014). On the other hand, margin trading increases stock market liquidity and price efficiency (Chordia et al., 2001; Alexander et al., 2004). The Chinese stock market lifts the constraints on margin trading and short selling in March 2010. Chinese evidence from the literature shows that allowing short selling and margin trading benefits price efficiency by incorporating negative information into stock prices (Chang et al., 2014). However, the landmark of margin-trading and short-selling activities evolved with the rapid increase in margin-trading activities. The second essay examines whether the margin-trading and short-sale activities and the associated substantial difference in trading volume cause stock misvaluation.

The second theme focuses on understanding whether the environmental, social and governance (ESG) score can affect stock misvaluation. Recent studies document that firm value and performance can be affected by the ESG score (Fatemi et al., 2015; Fatemi et al., 2018; Cao et al., 2021). Moreover, ESG information disclosure improves information transparency (Byard et al., 2006; Wong & Zhang, 2022; He et al., 2022). Beyond firm financial information, firm valuation may be affected by non-financial information. Furthermore, each pillar of ESG standing for a different aspect of a firm may affect firm valuation in different ways. The third essay investigates the influence of the ESG score and its pillars' score on stock misvaluation.

The remainder of this chapter is organised as follows. Sections 1.2 to 1.4 provide an overview and contributions to the literature of essays one, two, and three, respectively. Section 1.5 shows the research outputs. Section 1.6 presents the sequence of the remainder of the thesis.

1.2. Essay One

Compared with developed stock markets, the Chinese stock market is dominated by retailers who are less professional and knowledgeable than institutional investors. The first essay examines whether this causes stock misvaluation issues and generates return premiums.

Stock misvaluation could raise from market inefficiency and heterogeneous opinions of market participants. The studies of behavioural finance show evidence that common misvaluation exists in the stock market (Daniel et al., 2001; Shleifer, 2000). A stream of literature measures stock misvaluation in different ways. Hirshleifer and Jiang (2010) form a financing-based misvaluation measure based on debt and equity financing. Rhodes-Kropf et al. (2005) estimate firm intrinsic value from firm fundamental information. This method is applied by Chang et al. (2013) who measure stock misvaluation by taking the difference between actual and expected firm value. However, these measures may not be directly applied to developing markets which have different institutional structures compared with developed markets, as the distinct characteristics of developing market may affect the firm valuation. Further, developing markets with less efficient trading mechanisms and rules should have a more substantial misvaluation effect than developed markets.

The Chinese stock market, in which state ownership remains widespread, provides a suitable environment for our research purpose. Investors may have heterogeneous beliefs when they value SOEs and non-SOEs, as investors perceive the fact that SOEs are more protected by government. The SOEs receive financial supports from the government, which may signal to market that their financial performance is healthy. Moreover, individual investors occupy over 80% of trading volumes (Li & Wang, 2010; Yu et al., 2019). These investors are easily motivated by attention-grabbing events and primary market sentiment and therefore increase market volatility (Tian et al., 2018). In particular, the Chinese individual investors have the herding behaviour (Peikun & Jing, 2010). This irrational trading behaviour will create opportunities for stock misvaluation. Overall, the distinct ownership structure of Chinese firms and the composition of investors provide motivation for our research.

This essay modifies the method of Rhodes–Kropf et al. (2005) and Chang et al. (2013) by adding ownership classification in benchmark regressions to measure stock misvaluation. This measure caters to the institutional characteristics of the Chinese stock market. We find that the accounting variables of SOEs could explain more variation in firm value than for that of non-SOEs in misvaluation benchmark model. The misvaluation effect of SOEs is stronger than that of non-SOEs. This essay extends the work of Chang et al. (2013) by timing the misvaluation correction, finding that stock misvaluation is not persistent in the long run. The mispricing of SOEs corrects faster than that of non-SOEs. Moreover, we find that loadings on the misvaluation factor positively forecast the cross-section of returns in the rolling-window Fama-Macbeth two-stage regressions.

This essay makes three contributions to the literature on stock misvaluation. First, the essay highlights the importance of the influence of firms' ownership structures on stock valuation in the Chinese stock market. Second, it examines the timing of misvaluation correction, which has not been documented in the extant literature. Third, building on the literature on stock misvaluation, this essay points out the distinct market environment on the extent to which the Chinese misvaluation effect is significant.

1.3. Essay Two

Stock misvaluation could be caused by market constraint, which prevents stock prices from incorporating market information. Short sales constraint inhibits negative views of pessimistic investors and causes overvaluation (Miller,1977; Diamond & Verrecchia, 1987). Margin-trading ban hinders optimistic and aggressive investors from expressing positive opinions and decreases the market activity. From the supply and demand perspective, short sales increase the supply of stock on the market by the amount of the outstanding short position, leading to a shift of the supply curve to the right and a decrease in price (Miller, 1977). Margin trading moves the demand curve to the right, leading to a price increase.

The Chinese government relaxes the ban of margin trading and short selling in March 2010. Chang et al. (2014) document that short sellers, rather than margin traders, are information producers in the Chinese stock market. Short-selling activities enhance price efficiency by allowing stock prices to incorporate negative information. However, their finding is constrained by the data sample's timeframe, concluding in December 2012. Since December 2012, there has been a significant shift in the dynamics of margin trading and short selling, primarily due to a surge in margin-trading activities and the restricted availability of securities for lending. Acknowledging these changes in the market, we replicate the event study of Chang et al. (2014), extending the data sample up to the end of 2020 to reflect the current trading environment more accurately. We find positive (cumulative) abnormal returns, relative to the market-model predicted returns on the event trading day. This result, in contrast to Chang et al. (2014), illustrates that the intensified margin-trading activities have enabled abundant positive information to be incorporated by stock prices.

Motivated by the imbalanced development of margin trading and short selling and a distinct finding associated with this imbalanced trade, this essay intends to examine whether the imbalanced trading activities between margin traders and short sellers cause misvaluation, and how each influences the misvaluation. This essay shows that the imbalanced trading activities cause stock misvaluation by escalating overvaluation and reducing undervaluation. This effect is primarily derived from margin-trading activities, not short-selling activities. Even if short-selling activities benefit price efficiency by decreasing the stock overvaluation, the negative impact of short sellers on stock price is overwhelmed by positive information of margin traders whose trading volume dominates the total trading volume of the Chinese pilot programme.

This essay contributes to the literature by providing evidence that margin traders are information providers to a large degree, as margin trading corrects undervaluation. Moreover, the imbalanced development of margin-trading and short-selling activities has not been documented in the existing literature. This essay enhances the influence of imbalanced trading by margin traders and short sellers on misvaluation.

1.4. Essay Three

Environmental, social and governance (ESG) development has received increasing attention from investors. Developing firms' ESG practises is important, as it influences a firm's ability to attract sustainable investors and to raise capital. Firms with ESG practices also enrich information sources that investors can access and utilise to value stock.

A growing body of literature has uncovered evidence that improving a firm's ESG practices can enhance firm value and cause firm overvaluation, driven by investors with ESG preferences. This perspective aligns with the stakeholder theory, which suggests that companies should be responsible for all stakeholders rather than solely the interests of shareholders. Recent studies (for example, Bofinger et al., 2022) discover a positive correlation between ESG score and stock misvaluation in the US stock market. However, it remains unclear whether a similar positive association exists between ESG score and stock misvaluation in the Chinese stock market. In contrast to developed markets, China has embarked on its ESG initiatives relatively recently but has witnessed rapid growth. Furthermore, the investor composition of the Chinese stock market renders doubtful the positive effect of the ESG score observed in developed markets. This is because a significant portion of Chinese investors may not prioritise ESG programmes to the same extent as their counterparts in developed markets.

This essay investigates the relationship between the ESG performance of firms and stock misvaluation in the Chinese stock market. The result of this study reveals a negative correlation between ESG score and stock misvaluation. This negative effect could be attributed to the higher ESG disclosure, aligning with the notion that higher information transparency enhances price efficiency. However, ESG taken together may generate misleading regression results, as the overall ESG may offset the effect of each pillar of ESG on stock misvaluation. Each pillar of ESG measures different aspects a firm. Notably, the S (Social) score positively affects overvaluation, whereas the G (Governance) score negatively affects stock misvaluation by reducing overvaluation and undervaluation. Firms with better internal governance mechanisms help mitigate stock misvaluation, while those focusing on social activities receive higher investors valuations. We don't find any significant effect of the E (environmental) score on stock misvaluation.

This essay contributes to the literature in several ways. First, it comprehensively investigates the influence of overall ESG score and each individual ESG pillar on stock misvaluation. Second, the different impacts of the ESG pillars suggest that further separate investigations are necessary for each of pillars. Third, our findings underscore the importance of ESG information disclosure.

1.5. Research Output of the Thesis

Essay Two

The second essay, "The Impact of the Imbalanced Trades between Margin Trading and Short Selling on Stock Misvaluation: Evidence from the Chinese Pilot Program", was accepted to be presented at the 28th New Zealand Finance Colloquium 2024, The University of Auckland, New Zealand.

Essay Three

The third essay, "Stock Misvaluation and ESG: Evidence from China A-share Stock Market", was accepted to be presented at the 28th New Zealand Finance Colloquium 2024, The University of Auckland, New Zealand.

1.6. The Structure of the Thesis

The remainder of the thesis is structured as follows. Chapter 2 presents the first essay investigating the return predictive power of Chinese stock misvaluation. Chapter 3 presents the second essay, on the effect of margin-trading and short-selling activities on stock misvaluation. The third essay, on the relationship between ESG score and stock misvaluation, is presented in Chapter 4. Finally, Chapter 5 concludes the thesis by outlining the key findings and implications.

CHAPTER TWO

Misvaluation and Comovement in the Chinese Stock Market

ESSAY ONE

This chapter presents the first essay, which examines whether stock misvaluation and its risk premium exist in the Chinese stock market. The chapter is organised as follows. Section 2.1 introduces the background, motivation, and main findings. Section 2.2 reviews the literature. Section 2.3 presents the methodology and data sample. Section 2.4 shows the empirical results and analysis of the results. Section 2.5 concludes the first essay. The reference list for this chapter is included at the end of this thesis.

2.1. Introduction

Financial assets should be appropriately priced under the efficient-market hypothesis. However, numerous studies find that security prices cannot fully reflect all available information in the market, resulting in misvaluation. Misvaluation could be caused by market inefficiency and heterogeneous beliefs of market participants. Behavioural finance studies document the existence of common misvaluation in the stock market and, using various behaviour models, these studies show that misvaluation factors contain strong return predictive power. However, previous studies concentrate on developed markets. Few studies examine stock misvaluation in developing markets, such as the Chinese stock market, which is dominated by individual investors with behavioural bias. This chapter examines stock misvaluation and misvaluation comovement in the Chinese stock market. Our results contribute to the literature by adding new evidence through an examination of stock misvaluation in the Chinese stock market.

Based on the efficient-market hypothesis, asset prices should be determined by fundamental economic value. In an early article, Friedman (1953) states that rational market participants stabilise asset prices, while irrational investors will be driven out of the market, through being bankrupted by buying high and selling low. This argument is challenged by subsequent researchers of market efficiency (Figlewski, 1979; Kyle,1985; Campbell & Kyle, 1987; Delong et al., 1987). They document the inefficiency of the stock market caused by noise trading. These papers prompt the behavioural studies of asset misvaluation (for example, Daniel et al., 2001; Barberis & Shleifer, 2003). However, behavioural studies focus on examining the existence of common misvaluation across firms in equity markets, rather than measuring misvaluation. Hirshleifer and Jiang (2010) and Chang et al. (2013) measure US stock misvaluation using firms’ financing activity and firms’ fundamentals, respectively. They show strong empirical evidence supporting the existence of misvaluation in the US market and find the return predictive power of misvaluation factors, which are constructed by hedging portfolios based on the firm misvaluation.

Most studies examine the return predictive power of misvaluation in the US market. However, few researches are conducted in developing markets. Misvaluation should be more severe in developing markets, for several reasons. Firstly, most market participants in developing markets are more likely to be uninformed. A large amount of irrational trading may aggravate and cause stock misvaluation. Secondly, compared with mature markets, developing markets are at the early or growing stage of the financial market, which lacks a sound legal law and regulatory environment, and a full-order supervisory system. The Chinese market provides an ideal setting for studies on stock misvaluation because of its large trading volumes by individual traders with behavioural bias and its special trading mechanism. The Chinese market is dominated by individual investors who account for over 80% of market trading (Li & Wang, 2010; Yu et al., 2019). These individual traders could easily misinterpret public information and emotionally overreact to changes in public news, as they may lack professional knowledge and trading skills (Barber et al., 2009). Such investors are often defined as noise traders who frequently make irrational and erratic trading decisions. Moreover, Chinese individual investors with behavioural bias tend to choose young and high-tech companies to pursue high returns (Zhu & Niu, 2016). These characteristics of the Chinese stock market create the potential for severe stock misvaluation.

To improve the market price efficiency, the Chinese government implies the split-share structure reform to convert non-tradable shares to tradable shares in 2005. State-owned enterprises (SOEs) probably have more serious stock misvaluation than private firms. First, non-tradable shares directly or indirectly held by the Chinese government or government liked institutions prevent investors from expressing opinions through public trading. Hence, the market's opinions cannot be reflected in stock prices, which ultimately fail to motivate SOE managers to maximise shareholders' profits. Second, SOEs are more likely to benefit from low-interest loans and government subsidies than private companies, and especially from the economic stimulus packages (Harrison et al., 2019). Third, due to government control, SOEs tend to have serious information asymmetry and serious agency problems which hinder price discovery (Chernenko et al., 2012; Pantzalis & Park, 2014).

Although the above statements have shown that the Chinese stock market probably exhibits severe misvaluation, few studies[1] have investigated the relation between misvaluation and cross-sectional stock returns in the Chinese market. Also, motivated by the above mentioned institutional characteristics of the Chinese stock market, this study examines the misvaluation in the China A-share stock market. We compare the misvaluation effect between SOEs and non-SOEs.

In this chapter, we modify the model of Rhodes–Kropf et al. (2005) and Chang et al. (2013), by incorporating ownership classification in the cross-sectional misvaluation regression, to measure stock misvaluation (MSVF). This misvaluation measure is calculated as the difference between the real and expected intrinsic value of a firm. The magnitude of MSVF represents the extent of firm misvaluation. The further the value deviates from zero, the higher the price deviation. In particular, stocks with positive MSVF are defined to be overvalued, whereas those with negative MSVF are considered to be undervalued. This pricing deviation-based approach allows us to directly estimate firms' misvaluation and further observe stock characteristics and performances.

Before testing the return predictive power of MSVF, we examine stock characteristics within misvaluation deciles. We sort stocks into deciles based on MSVF and within each decile we observe firm characteristics such as firm age, earnings, dividend-payment and asset

[1] To our best know, Luo et al. (2015) examine the misvaluation in the Chinese stock market. However, they overlook the influence of a firm's ownership on estimating the firm value.

tangibility, etc. Generally, we find an increasing trend for profitability, dividend-payment, and firm size across misvaluation deciles. This finding suggests that highly mispriced stocks are large-size firms which are more likely to have positive earnings and pay higher dividends. Moreover, we observe the performance of stocks within each MSVF decile. We calculate the value-weighted stock returns in each decile and find that stocks from the bottom (undervalued) misvaluation decile outperform stocks from the top (overvalued) decile. After controlling conventional factors, the abnormal returns difference between the bottom and top deciles remains positive. We find that the return spread of SOEs is higher than non-SOEs, indicating a more serious misvaluation of SOEs.

We investigate the predictive power of MSVF on stock returns by using Fama-Macbeth regressions. We find loadings of MSVF to be negatively and significantly correlated with the cross-section of stock returns. After adding conventional return predictive variables, the sign of the premiums on MSVF remains negatively and statistically significant. This finding indicates that stock misvaluation is corrected by the market over time, as the misvaluation is perceived by investors who trade for profits and, therefore, mitigate the misvaluation.

Moreover, we form a misvaluation factor (MSV) by constructing a hedging portfolio associated with MSVF. We take a long position on the bottom 30%[2] of undervalued stocks and a short position on the top 30% overvalued stocks at the end of the fiscal year. MSV is the value-weighted portfolio. We find MSV has better performance in terms of returns and Sharp ratio, compared with all conventional factors. The return predictive power of MSV is not subsumed by conventional factors. Importantly, we investigate the misvaluation correction process and find the positive MSV return is indifferent from zero in the 31st holding month. This result means that stock misvaluation corrects in the third year after the portfolio formation

[2] Constructing portfolios by longing and shorting the bottom 30% and top 30% of stocks based on a specific firm characteristic is common in the literature. (for example, Chang et al., 2013).

and loses it return predictive power. We separate timing MSV of SOEs and non-SOEs, and find that the MSV formed by non-SOEs needs more time for market correction than for SOEs. The faster misvaluation correction of SOEs may be associated with faster revaluation of investors towards the news announcement on SOEs. The investors exaggerate the level of information asymmetry in SOEs, hence worsening the misvaluation due to their biased evaluation. When the hidden information is gradually released, they realize their bias and reevaluate more efficiently.

We test misvaluation comovement at both portfolio and individual stock levels and find consistent results. At the portfolio level, MSV and other factors are regressed on Fama-French 25 size-BM portfolios through the traditional Fama-Macbeth regression method. The premiums of MSV are positive and significant. At the individual stock level, stock returns are regressed on the loadings of MSV, controlling for a set of firm variables and risk factors. We also find the sign of MSV's premiums remains positive and significant. These findings indicate that portfolio return and stock return covariance with the misvaluation factor (MSV), captured by loadings on MSV are positively related to cross-sectional portfolio and stock returns, respectively.

Our study contributes to the literature as follows. First, we modify the misvaluation method of Rhodes–Kropf et al. (2005) in the Chinese stock market by adding ownership classification into our misvaluation benchmark regression. We argue that estimating stock misvaluation for the Chinese stock market should allow for the effect of SOE/non-SOE firm status. The misvaluation effect of SOEs is stronger than that of non-SOEs. Second, we extend the work of Chang et al. (2013) by further timing the misvaluation correction. Importantly, we show evidence that misvaluation corrects in the third year after portfolio formation as the return of MSV decreases over time. The misvaluation of SOEs corrects half a year earlier than that of non-SOEs. Our finding adds new evidence by examining stock misvaluation in developing countries.

2.2. Literature Review

2.2.1. Asset Pricing in Efficient and Inefficient Markets

Asset pricing is a traditional topic that has been discussed for many years. Based on the efficient-market hypothesis (EMH), the market price of financial assets should fully reflect all information available in the market (Fama, 1991). According to the EMH, no one can beat the market, because intensive competition quickly eliminates arbitrage opportunities. Moreover, the market price of assets should reflect their fundamental economic value. In other words, all financial assets in the efficient market environment are properly valued by market participants and there is no misvaluation of securities. Early support of the EMH comes from Friedman (1953), who maintains that rational market participants stabilize asset prices. While irrational investors will lose wealth and quickly go bankrupt through buying high and selling low, rational investors will eliminate the misvaluation and drive speculators out of the market. The following researchers on market efficiency and noise trading oppose Friedman's opinion: Figlewski (1979); Kyle (1985); Campbell and Kyle (1987); and Delong et al. (1987). They show empirical evidence and document that although rational trading can move asset prices towards fundamentals, rational traders cannot fully eliminate noise-driven price deviation.

Supporters of imperfect markets argue against the efficient-market hypothesis based on the existence of market frictions and constraints. These frictions and constraints include anomalies, asymmetric information, and short-selling constraints. Such anomalies as information cost and transaction cost will cause disequilibrium. Grossman and Stiglitz (1980) develop a model, in which make prices reflect information from informed to uninformed investors and identify market disequilibrium due to information cost. Constantinides (1986) show that transaction cost is sensitive to asset demand. Allen and Gorton (1993) state that portfolio manager trades are not only motivated by changes in information but also use asymmetric information to take advantage of other investors. The asset valuation model of Duffie et al. (2002) allows short sellers to search for security lenders and finds that asset prices are higher under short-selling constraints than without such constraints. Market inefficiency implies that the market is imperfect.

In an inefficient-market environment, market participants have different expectations regarding security prices, because investors cannot fully absorb market information (Shelifer, 2000). The trading decisions of investors differ based on the information they perceive. Consequently, the aggregated trades of investors with heterogeneous beliefs would ultimately affect security prices. This means that the market prices of financial securities reflect the heterogeneous beliefs of investors (Basak, 2005). In such an inefficient market environment, securities valuation is biased.

2.2.2. Behavioural Models on Misvaluation

The inefficiency of the stock market implies the existence of misvaluation, which can result from noise traders who probably misperceive macroeconomic news and are subject to cognitive biases. Nikolic and Yan (2014) present a well-documented explanation as to how overconfident investors relate to misvaluation. The following papers support the inefficient market theory and develop several behavioural models to examine the existence of common misvaluation in the US stock market. Daniel et al. (2001) introduce an overconfidence model. They state that investors may be overconfident about their capability for risk evaluation. Investors overacting to market information will lead to misvaluation across firms. Barberis and

Shleifer (2003) present a style-based portfolio selection model. Under the model specification, investors comove with the market factor and style factor. Common factors in asset returns are extracted based on the same style. Investor demands shift among asset groups, based on past performance and investor sensitivity to stock styles. Style stocks with good performance will be overvalued, and so generate low returns. Hence, this style model examines whether common shifts, which derive from style-driven investment demand, can cause common misvaluation. Barberis et al. (2005) use both univariate and bivariate regressions to investigate whether stock comovement comes from fundamental-based news or the sentiment of noise traders. They allow investors to adjust their exposures to stocks as their sentiment changes. As a result, they confirm that stock comovement reflects two types of information from both fundamental-based news and investor sentiment.

2.2.3. Characteristics of the Chinese Stock Market

The Chinese market provides a good example among developing markets for the study of stock misvaluation because it is dominated by individual investors. Less informed retail investors account for over 80% of trading volumes (Li & Wang, 2010; Yu et al., 2019). Individual investors are more likely than institutional investors to be subject to public information and overreact to macroeconomic news (Li et al., 2017; Nofsinger, 2001). Individual investors motivated by market-sentiment and attention-grabbing events exacerbate market volatility (Tian et al., 2018). Various studies have discussed the differences of trading behaviours between Chinese individual and institutional investors (for example, Ng & Wu, 2007; Peikun & Jing, 2010). Ng and Wu (2007) find Chinese institutions to be momentum investors, while individuals are contrarian investors. Both types of investors also have behaviour bias (Zhu & Niu, 2016). In particular, Chinese individual investors are more likely to invest in young and high-tech firms. As a result, this aggregated noise-driven trading will lead to large discrepancies between the market price of securities and their intrinsic value. This is because many individual investors do not properly value securities. In other words, noise trading of individual investors probably results in the misvaluation of financial assets.

Investors' herding behaviour also implies the existence of misvaluation, because asset valuation is more likely to be biased under herd trading. Lakonishok et al. (1992) have discussed the stabilising and destabilising effects of herding. Herding provides a possible explanation for the high volatility of the Chinese stock market. Tan et al. (2008) find investor herding in the Shanghai and Shenzhen exchanges for both A-share and B-share stocks. Peikun and Jing (2010) also find that both Chinese individual and institutional investors have herding behaviour, and the herding behaviour of individuals does not copy that of institutions. Different types of investors will have stabilising or destabilising effects on the market, because of differences in their trading behaviour. Tian et al. (2018) state that Chinese institutional investors systematically buy more than uninformed individual investors under extreme market conditions. They find institutional investors exert a stabilising effect on the market, especially during periods of market weakness. However, Chinese individual investors will destabilise the stock market (Li et al., 2017). Ren and Wu (2018) examine herding behaviour from an investor sentiment perspective. They find that pessimistic investors have a stronger tendency than optimistic investors to herd and confirm that macroeconomic information is important for individual investors' trading decisions.

2.2.4. State Owned Enterprise and Stock Misvaluation

Of all shares controlled by the Chinese government, 74% were forbidden to trade in the public market before 2005 (Liao et al., 2014). The non-tradable shares hinder price discovery, as various views of investors cannot be incorporated into stock prices through market trading.

Even if the Chinese government conducts split-share structure reform to improve market price efficiency, SOEs may have a more serious stock misvaluation issue than non-SOEs. First, compared with private companies, SOEs have relatively serious agency problems (Megginson, 2016). Manages of SOEs may contribute to fulfilling multiple firms' goals, rather than only maximising shareholders' interests, due to the interest conflict between the state and firms (Jiang & Kim, 2020). In contrast, private companies have stronger motivations to monitor managers and more efficient internal governance structure, thus reducing the self-interested behaviours of managers (Chen et al., 2011; Guan et al., 2021). Second, the stock misvaluation issue of SOEs may stem from higher information asymmetry. The increasing proportion of non-state shareholders decreases stock misvaluation by reducing the information asymmetry (Chernenko et al., 2012; Pantzalis & Park, 2014). This view is supported by Verrecchia (1983) who document that SOEs owned by non-state capital enhances the information disclosure quality. In addition, SOEs have more ease when accessing government subsidies and low-interest loans (Harrison et al., 2019). This benefit may mislead investors, so they more highly value these stocks when the government releases an economic stimulus package, ignoring the fact of inefficient capital allocation in SOEs. This will create a drift between the market price and intrinsic value. To sum up, stock prices of private firms are more sensitive to the market information that reflects heterogeneous beliefs of investors, which ultimately gives stronger incentives for, and pressures on, private firms to form more efficient corporate governance and information disclosure systems.

2.2.5. Methods of Measuring Misvaluation

The aforementioned studies show the existence of common misvaluation in the US market and the motivation to detect possible severe misvaluation in the Chinese equity market. However, they fail to quantitate the degree of stock misvaluation. Basically, misvaluation can be measured using two streams, one derived from internal and external financing activities, and the other generated through estimation based on firms' fundamentals. Hirshleifer and Jiang (2010) form a financing-based misvaluation measure, derived from repurchase decisions and new issuing activities. They identify common misvaluation across stocks based on debt and equity financing. Loadings on the misvaluation factor can predict both portfolio and stock returns. Additionally, Bottazzi et al. (2020) create a z-score as a misvaluation indicator based on the financing-based misvaluation factor. They use the z-sore to sort stocks and construct new valuation factors and find the z-score to have predictive power for future abnormal returns.

Rhodes-Kropf et al. (2005) create a new misvaluation measure, named the pricing deviation-based approach, by taking the difference between actual and expected firm value. This misvaluation measure reflects firm fundamentals information because it is estimated using three accounting variables taken within the same industry. Compared with the financing-based approach, this misvaluation measure approach is not subject to management behaviour and allows direct measurement of stock characteristics and performance. Chang et al. (2013) build on the research direction of Hirshleifer and Jiang (2010) and adopt the misvaluation measure of Rhodes-Kropf et al. (2005) to examine pricing deviation and misvaluation comovement. Their findings show that stock misvaluation (MSVF) has a strong ability to explain stock returns. They further form a misvaluation factor and find loadings of this specific factor to relate positively to portfolio returns.

2.3. Methodology and Data Sample Description

2.3.1. Misvaluation Measure

Our method of measuring individual stock misvaluation is based on the method of Rhodes–Kropf (2005). This misvaluation measure approximates a firm's intrinsic value in a backward-looking approach. In so doing, we first classify all stocks into 10 industry sectors based on the Bloomberg industry classification system and run the following cross-sectional regression for each industry and for each respective year in equation (2.1) (Chang et al., 2013). The method mentioned above demonstrates the way we follow Rhodes–Kropf (2005) and Chang et al. (2013). The following shows the way we modify their method to cater to the characteristics of the Chinese stock market. We add ownership classification into the above cross-sectional regressions. To this end, we categorise all stocks into a SOEs' group and a non-SOEs' group before running cross-sectional regressions within each industry on an annual basis. Hence, our estimated betas of a firm, and consequently, the estimated firm value, are derived from either the SOEs- or non-SOEs groups. Our estimated firm value that includes ownership information can provide more comprehensive insights, compared with the method of Rhodes–Kropf (2005), by considering the differences between SOEs and non-SOEs, enabling a more precise comparison of a firm's financial performance to its industry peers. The regression equation is defined as:

$$M_{i,t} = \beta_{0i,t} + \beta_{1i,t} B_{i,t-1} + \beta_{2i,t} Abs(NI)_{i,t-1} + \beta_{3i,t} I_{(<0)} \times Abs(NI)_{i,t-1} + \beta_{4i,t} LEV_{i,t-1} + \epsilon_{i,t} \quad (2.1)$$

where, i $\in$ SOEs when estimating the intrinsic value of SOEs on equation (2.1), and i $\in$ nonSOEs when estimating the intrinsic value of non-SOEs on equation (2.1). $M_{i,\,t}$ is the logarithm of firms' market value at the end (June) of fiscal year t. All independent variables are measured at the end of fiscal year t-1. B is the logarithm of the book value of common equity. $Abs(NI)$ is the absolute value for the logarithm of net income. $I_{(<0)}$ is defined as the dummy variable of net income. $I_{(<0)}$ equals to one when net income is negative, and zero otherwise. LEV is the leverage ratio, which is defined as the difference of one minus the common equity scaled by total assets.

The estimated dependent variable $\widehat{M_{i,t}}$ is treated as the forecasted intrinsic value of an individual firm in year t. Hence, the stock misvaluation can be calculated by taking the difference between the real firm value at each month of year t and the estimated intrinsic value, which is denoted as $MSVF_{i,t}$. The equation for calculating misvaluation is:

$$MSVF_{i,t} = M_{i,t} - \widehat{M_{i,t}} \tag{2.2}$$

MSVF[3] proxies for the dispersion degree between the real market value and estimated intrinsic value of an individual firm. The high absolute value of MSVF indicates that stocks are heavily mispriced by investors, and vice versa. Stocks with positive MSVF are defined as being overvalued, while stocks with negative MSVF are being undervalued.

2.3.2. Portfolio Construction

We directly obtain the daily and monthly market factor (MKT), size factor (SMB), book-to-market factor (HML) and monthly momentum factor (MOM) from the Chinese Stock Market & Accounting Research CSMAR database. To examine the misvaluation comovement in the China A-Share market, we also construct other four factors.

[3] We take the logarithm of firm market value in equation (2.1). Hence, MSVF is the difference between the logarithmic firm market value and the estimated value of the logarithmic firm value. MSVF can be treated as the logarithm of the ratio of firm market value over the estimated firm value. This misvaluation measure can predict future stock returns, as it is not a total dollar measure.

To construct the misvaluation factor (MSV), we follow Chang et al. (2013) and monthly sort stocks into deciles based on MSVF. We long the bottom 30% of stocks and short the top 30% of stocks to form a zero-investment hedging portfolio. In our main tables, this portfolio is held from July of the current calendar year t to June of calendar year t+1 and the portfolio return is value weighted on a monthly frequency. To test whether the return of MSV is sensitive to the length of holding periods, we also hold the MSV factor for different holding periods from 1 month to 36 months.

We construct the liquidity factor (LIQ) by using the liquidity ratio developed by Debata and Mahakud (2018). The liquidity ratio is defined as the absolute return scaled by turnover, which is the ratio of trading volume to the outstanding shares. There are two steps in the construction process. We first calculate the liquidity ratio for all stocks. Then, at the end of each June, we use the liquidity ratio to sort all stocks into high 30%, middle 40% and low 30% portfolios. To form the LIQ factor, we calculate the value-weighted returns of the difference between high-liquidity portfolios and low-liquidity portfolios.

Following Lyandres et al. (2008), we construct the investment factor (INV). Firstly, we calculate the investment-to-asset ratio (IVA) for each stock as the annual changes of property, plant and equipment (PPE) and inventory, scaled by the total assets. Secondly, at the end of each June, we divide all stocks into two groups based on the median size of the sample firms. Then, we use the investment-to-asset ratio to sort stocks into three groups; high 30%, middle 40% and low 30%. Finally, we take the intersection of the two size groups with the three investment-to-asset groups to form six portfolios. To form the INV factor, we calculate the value-weighted returns and take the difference between the simple average of the returns on high investment-to-asset portfolios and low investment-to-asset portfolios.

Leverage factor (LEV) is constructed by following Ferguson and Shockley (2003) and the construction involves 3 steps. In the first step, we calculate the leverage ratio for all stocks.

Lev is defined as the book value of total liabilities scaled by the market value of equity. The second step involves forming stock groups based on different characteristics. At the end of each June, we use the size, book-to-market ratio and leverage ratio to classify stocks into 3 groups; high 30%, median 40% and low 30%. In the last step, we take the intersection of all groups to form 27 portfolios and calculate the value-weighted return by taking the difference between the average returns on high- and low-leverage portfolios to form the final LEV factor.

2.3.3. Fama-Macbeth Regression

Fama-Macbeth regression is commonly used to examine whether risk factors can capture common risks. We follow Chang et al. (2013) to examine the return predictive power of loadings on stock misvaluation (MSVF) and misvaluation factor (MSV) by using the Fama-Macbeth regression. There are two stages in the Fama-Macbeth regression, time series regression and cross-sectional regression. We estimate the variables/factors betas via time-series regression for each stock or portfolio, which serves the further cross-sectional regression. We conduct the estimation using a rolling window approach.

In the first stage, we estimate betas on variables/factors in the time series regression. To conduct the regression, we first form an initial estimation period. We estimate variables/factors' betas over the fixed estimation period. These estimated loadings are treated as independent variables to feed the cross-sectional regression at the second stage. In other words, loadings are applied to the stock or portfolio returns over the next 12 months to estimate premiums on variables/factors in the cross-sectional regression. This procedure continues with the estimation period rolling forward monthly until the end of the data sample period. Additionally, we exclude stocks whose survival time is shorter than the length of the estimation period.

2.3.4. Data Sample Description

Our data sample includes all China A-share stocks listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE)[4], covering the period from December 2003 to December 2018. Our raw data starts from 2004[5], because there was a split-share structure reform in 2005. Before 2005, Chinese government agencies held about 74% of A-share stocks, which are not allowed to trade in the public market (Liao et al., 2014). Another reason for the use of the data sample period is that there is insufficient firm' data during the 1990s. Hence, investigating the most recent 15-year of A-share stocks has more significant implications for both academics and practitioners.

We obtain both daily and monthly stock returns and accounting data from the Chinese Stock Market & Accounting Research (CSMAR) database. Common equity with negative values is excluded from our data sample. The monthly risk-free rate is downloaded from the Wind database. We classify all A-share stocks into 10 industry sectors, based on the Bloomberg industry classification system, including communication, consumer discretionary, consumer staples, energy, financials, healthcare, industrials, materials, technology and utilities. Additionally, the daily and monthly market factor (MKT), size factor (SMB), book-to-market factor (HML) and monthly momentum factor (MOM) are also downloaded from CSMAR.

We use a wide range of control variables. ME is firms' market capitalisation. BM is the book-to-market ratio. Ret is the monthly stock return. AGE is the number of years since a stock first appears on the CSMAR database. MSVF is the stock misvaluation. NI is the net income. DE is the leverage ratio of Ferguson and Shockley (2003). IVA is the investment-to-asset ratio of Lyandres et al. (2008). AG represents the asset growth of Cooper et al. (2008). ACC is the

[4] We exclude B-share stocks, because the Chinese stock market is dominated by A-share stocks. Besides this, B-share stocks are only available for foreign investors and Chinese residents holding foreign currency. As a result, A-share stocks can be used as a representative data sample for researching the Chinese stock market.
[5] We treat 2004 as an initial year to construct factor portfolios in 2005.

operating accruals of Sloan (1996). ISSUE is the share issuance defined as the logarithm change of outstanding shares over a 1-year period, following Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility of Ang et al. (2006). IO is the institutional ownership, following Lin and Fu (2017). A summary of these variables is shown in Table 2.1.

Table 2.1. Summary of variables

	Mean	Median	Q1	Q3	Std.dev.
ME (in millions)	11661	4164	2098	8581	53516
BM	0.899	0.896	0.872	0.919	0.044
Ret	0.007	-0.002	-0.078	0.081	0.177
AGE	10	8	3	18	8
MSVF	0.001	0.002	-0.31	0.382	0.701
NI (in millions)	235	42	7	142	786
DE	0.775	0.368	0.139	0.94	1.001
IVA	0.012	0.003	-0.008	0.022	0.049
AG	0.011	0.006	-0.004	0.019	0.034
ACC	-0.007	0	-0.031	0.03	0.28
ISSUE	0.128	0	0	0.132	0.254
IVOL	0.019	0.017	0.012	0.024	0.011
IO	0.409	0.43	0.173	0.616	0.256

Notes: This table reports the mean, median, quarter one, quarter three values and the standard deviation of various variables, including market capitalisation (ME) reported in millions, book-to-market ratio (BM), stock return (Ret), firm age (AGE), stock misvaluation (MSVF), net income (NI) reported in millions, leverage ratio (DE), investment-to-asset ratio (IVA), asset growth (AG), operating accruals (ACC), share issuance (ISSUE), idiosyncratic volatility (IVOL) and institutional ownership (IO).

2.4. Results Analyses

2.4.1. Stock Misvaluation Within Each Industry

Table 2.2 shows stock misvaluation values of each industry. The mean values of stock misvaluation in most industries are positive, whereas the median values are negative, indicating the distribution of stock misvaluation in most industries is right skewed. It is interesting to note that the maximum and the minimum stock misvaluation occur in the financial industry. The financial industry also has the largest standard deviation and percentage of firms with positive misvaluation among industries. These extreme figures may indicate that stock pricing is not accurate enough in the financial industry which has comparatively much more intangible assets than other industries, because intangible financial assets are harder to value than are tangible assets, and the valuation is more likely to be subjective. In addition, the consumer discretionary industry shares similar characteristics with the financial industry, with respect to the minimum, standard deviation, positive and negative percentages of stock misvaluation.

Table 2.2. Description of industry misvaluation

Ind. Name	Ind.	Mean	Median	Min.	Max.	Std	Pos.	Neg.
Communications	1	-0.008	-0.021	-1.292	2.570	0.474	48%	52%
Consumer Discretionary	2	0.032	0.025	-4.822	3.163	0.862	52%	48%
Consumer Staples	3	-0.007	-0.022	-4.476	2.422	0.710	49%	51%
Energy	4	0.006	-0.017	-4.397	2.052	0.625	48%	52%
Financials	5	0.017	0.057	-4.857	4.099	0.890	54%	46%
Healthcare	6	0.041	0.024	-4.839	2.887	0.734	52%	48%
Industrials	7	0.008	-0.019	-4.523	3.935	0.684	48%	52%
Materials	8	0.018	-0.005	-4.458	2.541	0.701	50%	50%
Technology	9	0.019	-0.005	-4.111	2.758	0.694	50%	50%
Utilities	10	-0.001	-0.002	-3.289	1.943	0.549	49%	51%

Notes: This table shows the industry name, the original sector code of the Bloomberg Industry Classification System, the mean, the median, the minimum, the maximum, the standard deviation, the percentage of stocks with positive misvaluation and the percentage of stocks with negative misvaluation in each industry sector.

2.4.2. Benchmark Regression

We calculate stock misvaluation by estimating a firm's true value as a function of the book value of equity, net income and leverage. Table 2.3 reports the benchmark regression result based on equations (2.1) and (2.2).

Panel A shows coefficients on intercept and four variables based on the approach of Rhodes-Kropf et al. (2005) and Chang et al. (2013) using the whole data sample. We run regressions by year and industry and then calculate the mean value of the coefficients. We find that the book value of equity and net income are positively related to the market value of firms, while leverage is negatively associated with the stock market value. The coefficient sign is consistent with the finding of Rhodes-Kropf et al. (2005). We also show the time-series mean of coefficients in each industry. We find that the coefficients' sign in each industry's regression remains consistent with the one in overall regression. Though there are no perfect models that can estimate the exact firm values, the model we use provides a fair and reasonable estimated value and is serving the research purpose. The three accounting variables used in the model can explain over 50% within-industry variation of firm value on average.

Panels B and C reveal the coefficients of these four variables based on our modified approach of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Panels B and C show the estimated parameters of SOEs and non-SOEs, respectively. Generally, the coefficients' sign on each accounting variable in Panels B and C remains the same as in Panel A. When we include firms' ownership classification into the misvaluation benchmark regression, the explanatory power in the industry variation of SOE regression increases to 73.4%, while the adjusted R square for non-SOEs is just 28.35%. The higher the R square, the smaller the residual in regression, as the better explanatory power on variance reduces the deviation between the actual and estimated firm values. In general, the difference of the adjusted R square in the regressions suggests that the SOE and non-SOE classification affects the estimated intrinsic value of firms and, thus, the stock misvaluation. This parsimonious model helps us create sufficient cross-sectional dispersion of misvaluation. Individual stock misvaluation derived from this model has a strong predictive power for expected stock returns and a constructed MSV factor also inherits the misvaluation information contained in the misvaluation measure.

To compare the misvaluation of SOEs and non-SOEs, we conduct the t-test of misvaluation comparison in Panel D. The mean value of MSVF on SOEs is greater than that of non-SOEs. The misvaluation difference (0.2) is significant at the 1% significance level. This finding is held for 8 out of 10 industries, indicating that SOEs have more severe misvaluation than non-SOEs in most industries. The result of Panel D is consistent with the views of Chernenko et al. (2012) and Pantzalis and Park (2014), who document higher information asymmetry associated with agency cost on SOEs than non-SOEs, potentially leading to severe misvaluation.

Table 2.3. Benchmark regression

Panel A – Rhodes-Kropf et al. (2005)

Whole	Intercept	B	$Abs(NI)$	$I(<0)*\ Abs(NI)$	LEV	Adj. R	Obs.
	9.295***	0.453***	0.226***	-0.021***	-0.234***	50.62%	28612
	[36.56]	[32.42]	[29.3]	[-13.4]	[-7]		

Industry	Intercept	B	$Abs(NI)$	$I(<0)*\ Abs(NI)$	LEV	Adj. R	Obs.
1	9.141***	0.471***	0.226***	-0.022***	-0.124	67.40%	773
	[9.83]	[10.72]	[7.94]	[-4.9]	[-1.17]		
2	11.256***	0.355***	0.208***	-0.019***	-0.133**	28.91%	5129
	[26.31]	[13.8]	[11.65]	[-5.56]	[-2.45]		
3	7.005***	0.555***	0.25***	-0.025***	-0.392***	50.62%	1811
	[8.9]	[11.05]	[10.81]	[-7.05]	[-5.2]		
4	6.922***	0.622***	0.177***	-0.018***	-0.34**	72.27%	1186
	[11.34]	[16.7]	[5.43]	[-2.73]	[-2.25]		
5	7.349***	0.529***	0.233***	-0.014***	0.146	61.26%	2581
	[19.3]	[20.46]	[10.81]	[-3.58]	[1.46]		
6	9.242***	0.392***	0.311***	-0.013*	-0.556***	41.01%	2212
	[14.97]	[9.79]	[13.15]	[-1.84]	[-5.54]		
7	10.479***	0.424***	0.191***	-0.02***	-0.262***	45.70%	5676
	[19.07]	[13.57]	[16.55]	[-6.77]	[-3.59]		
8	9.976***	0.432***	0.213***	-0.022***	-0.375***	46.13%	4784
	[18.8]	[17.64]	[10.67]	[-6.95]	[-7.17]		
9	13.07***	0.265***	0.223***	-0.027***	-0.067	29.98%	3247
	[23.3]	[10.45]	[11.55]	[-7.35]	[-1.02]		
10	8.506***	0.483***	0.229***	-0.026***	-0.231**	62.91%	1213
	[12.21]	[11.59]	[9.71]	[-3.91]	[-2.09]		

Panel B - SOEs

	Intercept	B	$Abs(NI)$	$I(<0)*Abs(NI)$	LEV	Adj. R	Obs.
	7.423***	0.552***	0.222***	-0.016***	-0.2***	73.40%	13083
	[36.81]	[41.73]	[24.82]	[-9.19]	[-5.91]		

Industry	Intercept	B	$bs(NI)$	$I(<0)*Abs(NI)$	LEV	Adj. R	Obs.
1	8.618***	0.417***	0.318***	-0.009	-0.424***	76.35%	306
	[11.89]	[7.55]	[8.76]	[-0.84]	[-3.35]		
2	7.248***	0.607***	0.166***	-0.012***	-0.308***	68.62%	2229
	[17.44]	[24.62]	[14.9]	[-3.76]	[-5.67]		
3	5.741***	0.584***	0.292***	-0.019***	-0.338***	70.94%	931
	[7.86]	[11.62]	[10.59]	[-6.12]	[-3.72]		
4	5.69***	0.662***	0.193***	-0.021***	-0.106	87.23%	615
	[18.52]	[18.76]	[5.97]	[-3.7]	[-0.85]		
5	7.368***	0.544***	0.224***	-0.011***	0.196**	80.49%	1336
	[15.56]	[21.14]	[12.53]	[-4.06]	[2.48]		
6	7.876***	0.459***	0.314***	0	-0.489***	65.89%	771
	[12.78]	[12.21]	[14.13]	[-0.04]	[-5.18]		
7	7.755***	0.583***	0.166***	-0.018***	-0.22***	68.62%	2523
	[15.81]	[19.61]	[10.39]	[-7.17]	[-3.68]		
8	7.556***	0.561***	0.205***	-0.026***	-0.269***	71.51%	2494
	[16.79]	[19.47]	[9.41]	[-6.79]	[-4.79]		
9	9.759***	0.467***	0.189***	-0.023***	0.068	59.23%	950
	[15.09]	[12.17]	[9.42]	[-9.33]	[0.62]		
10	6.617***	0.641***	0.156***	-0.017***	-0.11	85.16%	928
	[11.29]	[22.51]	[8.41]	[-3.77]	[-1.15]		

Panel C - Non-SOEs

	Intercept	B	$Abs(NI)$	$I(<0)* Abs(NI)$	LEV	Adj. R	Obs.
	13.012***	0.232***	0.256***	-0.027***	-0.295***	28.35%	15529
	[33.14]	[9.66]	[19.16]	[-8.92]	[-4.66]		

Industry	Intercept	B	$Abs(NI)$	$I(<0)* Abs(NI)$	LEV	Adj. R	Obs.
1	10.424***	0.418***	0.207***	-0.024***	-0.133	37.35%	467
	[11.65]	[9.63]	[5.38]	[-3.36]	[-0.94]		
2	16.164***	0.062	0.243***	-0.026***	-0.128*	15.38%	2900
	[21.74]	[1.58]	[9.58]	[-4.74]	[-1.92]		
3	9.607***	0.466***	0.2***	-0.036***	-0.649***	29.44%	880
	[11.8]	[10.03]	[7.74]	[-6.03]	[-4.68]		
4	10.099***	0.442***	0.197***	-0.021**	-0.281	37.41%	571
	[9.32]	[7.28]	[4.01]	[-2.14]	[-0.85]		
5	8.302***	0.47***	0.233***	-0.016**	0.137	43.21%	1245
	[9.79]	[11.04]	[7.9]	[-2.27]	[0.88]		
6	9.859***	0.31***	0.369***	-0.015	-0.703***	33.88%	1441
	[10.47]	[4.43]	[9.75]	[-1.37]	[-4.1]		
7	16.075***	0.126***	0.188***	-0.021***	-0.047	16.63%	3153
	[23.03]	[3.81]	[9.73]	[-4.44]	[-0.48]		
8	16.235***	0.067	0.255***	-0.017***	-0.46***	17.78%	2290
	[23.51]	[1.42]	[8.07]	[-2.83]	[-4.92]		
9	16.639***	-0.003	0.31***	-0.03***	-0.034	23.13%	2297
	[24.57]	[-0.05]	[9.66]	[-5.13]	[-0.48]		
10	16.714***	-0.041	0.358***	-0.062***	-0.656*	29.24%	285
	[18.82]	[-0.5]	[4.88]	[-3.5]	[-1.89]		

Panel D – T-test for the misvaluation difference of SOEs and Non-SOEs

Whole	SOEs	Non-SOEs	Diff (MSVF)	t(diff)
	0.108	-0.091	0.2***	[22.72]

Industry	SOEs	Non-SOEs	Diff (MSVF)	t(diff)
1	-0.024	0.016	-0.04	[-1.11]
2	0.182	-0.140	0.321***	[13.82]
3	0.100	-0.106	0.206***	[5.93]
4	0.012	-0.013	0.024	[0.62]
5	0.157	-0.169	0.326***	[8.94]
6	0.044	-0.023	0.067**	[2.31]
7	0.075	-0.060	0.135***	[7.25]
8	0.104	-0.113	0.217***	[9.98]
9	0.166	-0.069	0.235***	[9.71]
10	0.076	-0.247	0.323***	[4.88]

Notes: This table includes four panels. The Panel A result is based on the approach of Rhodes-Kropf et al. (2005) and Chang et al. (2013) using the whole data sample. Panels B and C reports the regression parameters of SOEs and non-SOEs, based on our modified approach of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Each reports the average coefficients, including B, $Abs(NI)$, $I(<0)*Abs(NI)$ and LEV. B is the logarithm of the book value of common equity, for the whole and within each industry. $Abs(NI)$ is the absolute value for the logarithm of net income. $I(<0)$ is defined as the dummy variable of net income. $I(<0)$ equals to one, when net income is negative and zero otherwise. LEV is the leverage ratio, which is defined as the difference of one minus the common equity scaled by total assets. Panel D reports the t-test for the misvaluation difference of SOEs and Non-SOEs. The t-value of Table 2.3 is calculated using Newey-West standard errors with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

2.4.3. Stock Characteristics

Baker and Wurgler (2006) suggest that the valuation of stocks with similar characteristics is more subjective and more likely to be biased. Hence, we examine stock characteristics under misvaluation deciles, before testing the predictability of misvaluation. We sort stock misvaluation into deciles at the end of each June and observe the average value of stock characteristics under each decile in Table 2.4. Panels A, B and C of Table 2.4 report the stock characteristics of all firms, SOEs and non-SOEs, respectively.

In Panel A of Table 2.4, M1 and M10 contain the most mispriced stocks, with a degree of misvaluation of -0.782 and 1.158, respectively. The value of MSVF in M5 approaches 0, indicating that the real firm market value is close to the expected firm value. The difference of MSVF between M10 and M5 is 1.218. Not surprisingly, this figure increases to 1.94 when, taking the difference between M10 and M1.

Rows from (2) to (5) report the average stock characteristics, including firm age, the proportion of firms with positive earnings and dividend-payment, and the fixed asset proportion. In the second row, stocks in M1 are dominated by long-history firms, with an average age of 9.227 years. The firm age decreases along deciles until M9 and then slightly rises with deciles. The AGE difference between M10 and M1 is -1.298, showing that mature companies are more likely to be undervalued by investors, and vice versa. The reason for this may be that young firms with greater growth potential, compared with well-established firms, attract Chinese investors who pursue a long-term gain. Start-ups are more likely to receive financial supports from government, making them more attractive. Rows (3) and (4) show that most Chinese firms are profitable and over half of firms pay dividends. Compared with other deciles, M1 of both rows (3) and (4) shows the smallest proportion of firms with positive earnings and dividend payments. The differences of M10 minus M1 for earnings and dividends are 0.048 and -0.061, respectively. This implies that overvalued firms are more likely to earn profits and pay dividends to shareholders. The reason could be that firms with healthy financial conditions and mature dividend policies catch the attention of Chinese investors. Interestingly, FA/A shows a decreasing trend along deciles. The lack of tangible assets would lead firms to be overvalued.

The last three rows reflect firm size, book-to-market and the past performance of firms across misvaluation deciles. Generally, ME increases with misvaluation deciles, while BM decreases with misvaluation deciles. The reason is likely to be that Chinese investors tend to invest in large and high-growth companies. In addition, we don’t find a significant difference of MOM in most over- and undervalued deciles.

The figures of stock characteristics across misvaluation deciles are shown in Figure 2.1 The stock characteristics in all figures are consistent with the above description in Table 2.4. Generally, Panel B, Panel E, and Panel G have decreasing trends along misvaluation deciles, indicating that stocks with high misvaluation are young firms with less tangible assets and lower book-to-market values. On the contrary, Panel C, Panel D and Panel F have increasing trends along misvaluation deciles, revealing that overvalued stocks tend to be large firms, which are more likely to earn profits and pay dividends.

Panels B and C show similar performances of stock characteristics as Panel A. Generally, the value of AGE, FA/A, ME, and MOM of SOEs under each decile are higher than that of non-SOEs, suggesting that SOEs are longer-history and larger-size firms with greater proportion of fixed asset and better past stock performance.

Table 2.4. Stock characteristics under stock misvaluation deciles

Panel A – whole sample

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M10-M5	t-stat.	M10-M1	t-stat.
(1) MSVF	-0.782	-0.485	-0.317	-0.187	-0.060	0.067	0.212	0.393	0.627	1.158	1.218***	[105.48]	1.94***	[167.96]
(2) AGE	9.227	8.560	8.409	8.257	8.060	8.008	7.890	7.610	7.654	7.929	-0.131	[-0.28]	-1.298***	[-2.76]
(3) E+	0.841	0.875	0.881	0.883	0.883	0.896	0.890	0.889	0.893	0.889	0.006	[0.59]	0.048***	[4.53]
(4) D+	0.581	0.586	0.611	0.611	0.623	0.622	0.659	0.646	0.669	0.642	0.019	[0.97]	0.061***	[3.07]
(5) FA/A	0.448	0.440	0.436	0.433	0.428	0.423	0.418	0.408	0.397	0.391	-0.037***	[-4.2]	-0.057***	[-6.47]
(6) ME	4569	5373	6948	9411	9858	11003	14258	17240	18392	23452	13594***	[6.88]	18883***	[9.56]
(7) BM	0.912	0.903	0.900	0.897	0.894	0.892	0.887	0.884	0.880	0.872	-0.023***	[-12.46]	-0.04***	[-22.14]
(8) MOM	0.082	0.081	0.094	0.083	0.087	0.080	0.079	0.073	0.068	0.077	-0.01	[-0.83]	-0.005	[-0.43]

Panel B – SOEs

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M10-M5	t-stat.	M10-M1	t-stat.
(1) MSVF	-0.79	-0.49	-0.32	-0.19	-0.06	0.07	0.21	0.39	0.62	1.13	1.195***	[74.01]	1.924***	[119.16]
(2) AGE	10.968	10.932	10.561	10.590	10.041	9.994	9.796	9.473	9.329	9.561	-0.48	[-0.85]	-1.406**	[-2.48]
(3) E+	0.857	0.856	0.863	0.876	0.866	0.892	0.886	0.859	0.885	0.880	0.014	[0.98]	0.024	[1.63]
(4) D+	0.610	0.543	0.584	0.601	0.614	0.616	0.659	0.629	0.686	0.660	0.046*	[1.74]	0.049*	[1.88]
(5) FA/A	0.484	0.478	0.462	0.464	0.454	0.451	0.444	0.435	0.420	0.412	-0.042***	[-3.78]	-0.072***	[-6.47]
(6) ME	5681	6131	9132	13145	13593	15811	20523	28280	31003	35332	21740***	[6.34]	29651***	[8.65]
(7) BM	0.922	0.910	0.908	0.904	0.900	0.896	0.891	0.887	0.880	0.869	-0.032***	[-15.72]	-0.053***	[-26.32]
(8) MOM	0.094	0.090	0.110	0.097	0.092	0.088	0.074	0.081	0.093	0.080	-0.011	[-0.64]	-0.014	[-0.76]

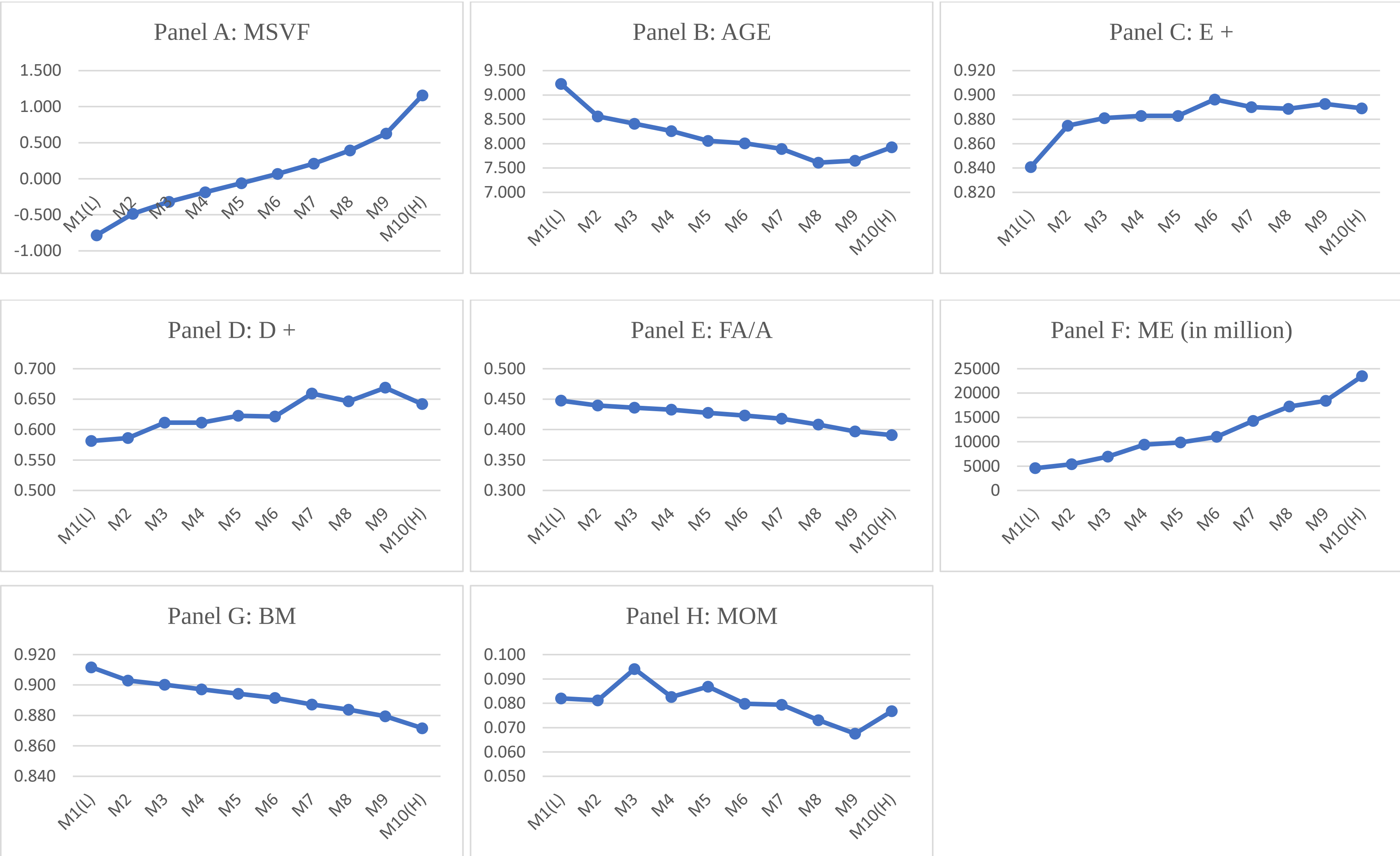
Panel C – Non-SOEs

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M10-M5	t-stat.	M10-M1	t-stat.
(1) MSVF	-0.771	-0.485	-0.319	-0.188	-0.059	0.067	0.212	0.394	0.629	1.176	1.235***	[70.07]	1.947***	[110.48]

(2) AGE	7.211	5.947	5.776	6.124	6.179	6.225	6.343	6.362	6.740	7.166	0.988	[1.53]	-0.045	[-0.07]
(3) E+	0.794	0.874	0.905	0.875	0.898	0.893	0.885	0.913	0.892	0.893	-0.005	[-0.28]	0.099***	[5.93]
(4) D+	0.484	0.603	0.645	0.596	0.613	0.615	0.641	0.647	0.645	0.626	0.014	[0.43]	0.142***	[4.46]
(5) FA/A	0.393	0.394	0.400	0.393	0.396	0.393	0.392	0.385	0.379	0.381	-0.015	[-1.29]	-0.013	[-1.06]
(6) ME	2881	3944	3797	4299	5530	5431	7706	8556	10539	17174	11644***	[6.37]	14293***	[7.82]
(7) BM	0.898	0.893	0.890	0.890	0.888	0.888	0.885	0.882	0.881	0.874	-0.014***	[-5.17]	-0.024***	[-8.69]
(8) MOM	0.062	0.068	0.067	0.065	0.089	0.064	0.087	0.068	0.054	0.073	-0.016	[-0.97]	0.011	[0.63]

Notes: This table reports stock characteristics across misvaluation deciles from M1(L) to M10(H). M1 includes the most undervalued stocks, while M10 contains the most overvalued stocks. The differences of stock characteristics between M10 and M5, as well as M10 and M1, are reported in this table. MSVF is the stock misvaluation, which is calculated through our pricing deviation-based approach. AGE is the number of years since the initial public offering of a company. E+ is defined as the percentage of firms with positive earnings. D+ is defined as the percentage of firms paying dividends. FA/A is the fixed asset over total asset. ME is reported in millions and is defined as firms' market capitalisation. BM is the book-to-market ratio. MOM is stock returns over the past 12 months. Panels A, B and C report stock characteristics of all firms, SOEs and non-SOEs, respectively. The t-value is calculated using Newey-West standard errors with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

Figure 2.1. Stock characteristics across misvaluation deciles



Notes: These figures show the stock characteristics across misvaluation deciles for all firms. We sort all stocks into deciles based on stock misvaluation (MSVF) each year. In each decile, we calculate the average value of firm characteristics, including stock misvaluation (MSVF), firm age (AGE), percentage of firms with positive earnings (E+), percentage of firms with dividend payments (D+), fixed assets scaled by total assets (FA/A), firm size (ME), book-to-market ratio (BM), and return over the past 12 months (MOM).

2.4.4. Stock Return Predictive Rower of MSVF

We examine the relation between MSVF and future stock returns in this section. Firstly, we perform a pre-test based on the sort of MSVF to observe raw returns and abnormal returns of misvaluation decile portfolios, controlling conventional factors. Secondly, we conduct Fama-Macbeth regression to further analyse the return predictive power of MSVF.

2.4.4.1. Pre-test of Sorting MSVF

In the pre-test, we sort stocks into 10 groups based on the MSVF at the end of each June and calculate the value-weighted portfolio returns over the next 12 months. In other words, each decile portfolio is held from July of the current calendar year T_0 to June of the next calendar year T_1. Then, the 10 portfolios are rebalanced, with the stocks resorted by updating MSVF in June of T_1, with respect to the information change of market and firms. In Table 2.5, we calculate the time-series average raw returns of the deciles over the period from 2005 to 2018. We also filter out the return predictive information contained in conventional factors. Technically, we calculate the time-series average abnormal return of each decile by regressing decile portfolio returns on conventional factors, such as the market factor, Fama-French three factors and Fama-French three factors plus the momentum factor. We find that the bottom decile outperforms the top decile, controlling conventional factors. These results are shown in Table 2.5.

Table 2.5. Raw return and Alphas based on sort of $MSVF$

Panel A: Whole sample

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M1-M10	t-stat.
Raw ret	3.569	3.263	2.462	2.225	1.712	1.303	0.673	0.193	-0.440	-1.577	5.145***	[16.63]
Capm	0.683	0.479	-0.084	-0.308	-0.862	-0.962	-1.304	-1.668	-1.985	-2.438	3.121***	[16.29]
Fama α	0.269	0.174	-0.148	-0.215	-0.612	-0.672	-0.750	-1.079	-1.173	-1.355	1.623***	[10.91]
FaMo α	0.221	0.147	-0.134	-0.201	-0.562	-0.609	-0.661	-0.977	-1.024	-1.184	1.405***	[9.68]

	SIZE (quintiles)					BM (quintiles)				
	S	2	3	4	B	L	2	3	4	H
L-H	0.514	2.634***	2.271***	2.176***	2.178***	0.331***	0.251***	0.362***	0.353***	0.355***
t-stat.	[1.11]	[5.38]	[5.38]	[6.41]	[4.62]	[4.37]	[3.47]	[4.99]	[5.79]	[5.35]

Panel B: SOEs

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M1-M10	t-stat.
Raw ret	3.975	2.977	2.608	2.118	1.940	1.545	0.860	0.034	-0.471	-1.366	5.341***	[11.96]
Capm α	1.818	1.437	1.129	0.584	0.402	-0.034	-0.410	-0.978	-1.348	-2.003	3.821***	[14.97]
Fama α	0.595	0.434	0.281	-0.038	-0.069	-0.336	-0.504	-0.921	-1.065	-1.400	1.995***	[10.49]
FaMo α	0.536	0.350	0.177	-0.144	-0.160	-0.409	-0.486	-0.868	-0.939	-1.261	1.797***	[9.6]

	SIZE (quintiles)					BM (quintiles)				
	S	2	3	4	B	L	2	3	4	H
L-H	1.897***	2.401***	2.106***	1.988***	1.897***	0.323***	0.354***	0.315***	0.261***	0.267***
t-stat.	[3.87]	[4.09]	[4.87]	[4.94]	[3.8]	[4.62]	[3.83]	[4.53]	[4.53]	[2.78]

Panel C: Non-SOEs

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M1-M10	t-stat.
Raw ret	2.970	3.477	2.313	2.088	1.564	0.883	1.032	0.345	-0.560	-1.799	4.77***	[11.52]
Capm α	0.099	0.042	-0.458	-0.528	-1.120	-1.318	-1.394	-1.816	-2.189	-2.676	2.775***	[10.3]
Fama α	0.017	-0.016	-0.289	-0.242	-0.704	-0.762	-0.775	-0.969	-1.235	-1.412	1.429***	[6.83]
FaMo α	0.055	0.024	-0.180	-0.182	-0.574	-0.633	-0.664	-0.849	-1.034	-1.220	1.275***	[6.32]

	SIZE (quintiles)						BM (quintiles)				
	S	2	3	4	B		L	2	3	4	H
L-H	-0.354	1.391***	2.078***	2.429***	2.321***		0.285***	0.169**	0.256***	0.285***	0.024
t-stat.	[-0.64]	[3.12]	[5.31]	[4.23]	[4.18]		[3.2]	[2.29]	[3.74]	[3.31]	[0.34]

Notes: There are three panels in this table. The result in Panel A is based on the MSVF constructed by the approach of Rhodes-Kropf et al. (2005) and Chang et al. (2013) using the whole data sample. The result of Panels B and C is based on the MSVF measured by our modified misvaluation approach. Each panel reports the raw returns and abnormal returns under MSVF deciles, controlling for the market factor, Fama-French three factors and Fama-French three factors plus the momentum factor. The return differences between the bottom and top portfolios, as well as corresponding t statistics, are also reported. Each panel also reports the time-series average of abnormal return differences between the bottom and top misvaluation deciles, which are constructed using two steps. In Step 1, the stocks are sorted into quintiles by firm size (book-to-market) and then sorted into deciles based on MSVF at the end of each June. In Step 2, the abnormal returns are estimated by regressing the decile returns on conventional variables, including the Fama-French 3 factors and the Momentum factor. The bottom left of each panel reports the abnormal return of the difference between the low and high misvaluation portfolio for each size quintile. The bottom right of each panel reports the abnormal return of the difference between the low and high misvaluation portfolio for each book-to-market quintile. The t-value is calculated using Newey-West standard errors with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

In Panel A of Table 2.5, raw returns monotonously decrease across MSVF deciles. In detail, the raw return of M1 (most undervalued stocks) is 3.569%, while the raw return of M10 (most overvalued stocks) is -1.577%. The return difference between M1 and M10 is 5.145%, with a t-value of 16.63. This finding is robust after adjusting for conventional factors. Abnormal returns monotonically decrease across MSVF deciles. The positive return difference between M1 and M10 indicates that buying the most undervalued stocks, while selling the most overvalued stocks can earn significant profits. The return spread in China is four times higher than in the US stock market (1.234%) documented by Chang et al. (2013). The difference in return spread indicates that the misvaluation effect is stronger in the Chinese than in the US stock market. The underlying reason may relate to the characteristics of the Chinese stock market, which is dominated by individual investors (Li & Wang, 2010). These investors are more likely to overact macroeconomic news, leading to severe misvaluation in China (Li et al., 2017).

We also conduct a double-sorted regression based on firm market capitalisation and book-to-market ratio, and further confirm that the return predictive power of MSVF is not simply derived from these two variables. The reason why we want to eliminate any possible influences of firm size and book-to-market ratio is that the findings of Table 2.4 suggest MSVF may be correlated with these two variables. Practically, we first sort stocks into quintiles based on firm size (book-to-market) and further sort them into quintiles based on MSVF to form 25 portfolios at the end of each June. Then we regress quintile returns against the Fama-French 3 factors and momentum factor to get abnormal returns (Alphas). Finally, we calculate the time-series mean of abnormal returns and take the difference in each size (book-to-market) group by using the bottom MSVF portfolio minus the top MSVF portfolio. We find the return difference between low and high MSVF stocks is positive and significant across all size and

BM quintiles. This finding indicates that the return predictive power of MSVF is not subsumed by firm size and BM.

Panels B and C compare the return spread between SOEs and non-SOEs. We can see that the spread of SOEs is higher than that of non-SOEs, reflecting that the misvaluation effect in SOEs is stronger. This finding is robust when controlling conventional factors. The underlying reason is that SOEs, which have less transparent information and less efficient internal governance, are more likely to be misvalued by investors compared to non-SOEs. However, this does not necessarily imply that the correction[6] of stock misvaluation for SOEs is slower than for non-SOEs. In cases where investors effectively utilise the information related to SOEs and are more efficient in their assessments compared to non-SOEs, misvaluation in SOE stocks can be corrected at a faster pace.

2.4.4.2. Fama-Macbeth Regression

The results of Table 2.5 have indicated that MSVF may contain stock return predictive power. In this section, we follow Chang et al. (2013) and use Fama-Macbeth regression to further explore the relation between MSVF and stock returns. Loadings of independent variables at time t are applied to the next period stock return at t+1. To alleviate the concern that the return predictive information of MSVF is not possibly contaminated by conventional firm variables, we include various control variables in the following equation:

[6] In section 2.4.5, we investigate the process of misvaluation correction. Specifically, we compare the misvaluation correction of SOEs and non-SOEs.

$$Ret_{i,t} = b0_{i,t} + b1_{i,t}MSVF_{i,t} + b2_{i,t}LOGME_{i,t} + b3_{i,t}LOGBM_{i,t} + b4_{i,t}RET_{m-1_{i,t}} + b5_{i,t}RET_{m-12,m-2_{i,t}} + b6_{i,t}ISSUE_{i,t} + b7_{i,t}ACC_{i,t} + b8_{i,t}AG_{i,t} + b9_{i,t}IVA_{i,t} + b10_{i,t}IVOL_{i,t} + b11_{i,t}IO_{i,t} + \epsilon_{i,t} \quad (2.3)$$

where Ret is the monthly stock return, and MSVF is stock misvaluation. $LOGME$ is the logarithm of market capitalisation. $LOGBM$ is the logarithm of the book-to-market ratio. RET_{m-1} is the return of the past one month. $RET_{m-12,\,m-2}$ represents the momentum and is calculated as the cumulative return from month $m-12$ to month $m-2$. $ISSUE$ is the share issuance of Pontiff and Woodgate (2008). ACC is the operating accruals, following Sloan (1996). AG is the asset growth of Cooper et al. (2008). IVA is the investment-to-asset ratio developed by Lyandres et al. (2008). $IVOL$ is the idiosyncratic volatility of Ang et al. (2006). IO is the institutional ownership of Lin and Fu (2017). Additionally, industry dummies are also included in this regression.

To mitigate the concern that the return predictive power of stock misvaluation is driven by conventional risk factors, we also control the loadings of the Fama-French 3 factors. To this end, we first form 100 portfolios based on the intersection of size and book-to-market ratio deciles at the end of each June. Second, we regress the value-weighted portfolios' returns on these 3 factors; market, size, and book-to-market; over the 36-month estimation period. Finally, betas of these 3 factors are applied to stocks in the portfolio to predict stock returns over the next month in the cross-sectional regression.

Table 2.6 includes eleven regressions, in which control variables are added in sequence. In the first regression, we use MSVF as the sole independent variable. We find a negative sign on MSVF, indicating that stock misvaluation could correct over time. This finding is consistent with the negative sign on MSVF found by Chang et al. (2013). The premium of MSVF is -

3.468, which is statistically and significantly different from zero at the 1% level (t= -3.82). This means that one standard deviation increase in stock misvaluation (0.311) will lead to a 1.078% decrease in monthly stock returns. A standard deviation increase in MSVF would reduce future stock return by 0.33% in the US stock market (Chang et al., 2013). This different finding confirms that the effect of MSVF on future stock returns is stronger in the Chinese than in the US stock market. This result is also consistent with the return spread finding in Table 2.5.

In the second regression, MSVF and another four control variables are included; LOGME, LOGBM, RET_{m-1}, and $RET_{m-12,\ m-1}$. We find that the premium MSVF remains negative and statically significant at the 5% level (t=-2.39). LOGBM, short period stock return (RET_{m-1}) and momentum ($RET_{m-12,\ m-1}$) also show return predictive power, with a negative sign for RET_{m-1} and positive signs for LOGBM and $RET_{m-12,m-1}$. Book-to-market and stock momentum contain stock return predictive power. In regressions 3 to 6, we add ISSUE, ACC, AG, IVA, IVOL and IO in sequence. The signs of MSVF premiums remain significantly negative and their magnitudes do not change by much. These findings suggest that the return predictive power of loadings on MSVF is not subsumed by these variables. Moreover, the signs of premiums for LOGME, RET_{m-1} and $RET_{m-12,\ m-1}$ do not reverse and remain significant in regressions 3 to 6. Among these newly added variables, none show significant premiums. This implies that their loadings do not have the predictive power for the future cross-section stock return in the Chinese stock market. In regression 8, we include all variables in the regression and find that the sign of MSVF's premium remains negative and statistically significant at the 1% level. In the last regression, we exclude LOGBM and find the sign of MSVF's premium does not flip, remaining statistically significant. The result reflects that the return predictive power of MSVF does not rely on the book-to-market ratio. Through the horse race test of Table 2.6, we find that loadings of MSVF are negatively and significantly related to cross-sectional future stock returns.

Table 2.6. MSVF performance in Fama-Macbeth regressions

	1	2	3	4	5	6	7	8	9	10	11
intercept	0.24	-1.285**	-1.225**	-1.586***	-1.581***	-1.709***	-1.445***	-1.904***	-1.23***	-4.142***	-4.475***
	[0.34]	[-2.28]	[-2.22]	[-2.69]	[-3.77]	[-4.1]	[-5.09]	[-3.18]	[-3.06]	[-3.23]	[-18.82]
β_{MSVF}	-3.468***	-0.947**	-0.657*	-0.785**	-0.773**	-0.734***	-0.324*	-1.276**	-0.755*	-0.508**	-4.667***
	[-3.82]	[-2.39]	[-1.69]	[-2.23]	[-2.45]	[-2.88]	[-1.78]	[-2.29]	[-1.7]	[-2.05]	[-27.05]
β_{LOGME}		0.421*	0.151***	0.32**	0.39***	0.454**	0.111**	0.341**	0.455	2.731***	-0.603*
		[1.68]	[2.64]	[2.03]	[2.86]	[2.5]	[2.4]	[2.16]	[1.2]	[4.34]	[-1.88]
β_{LOGBM}		0.016	0.068*	0.01	0.011	0.004	-0.026	0.034**		0.021	
		[0.82]	[1.79]	[0.53]	[1.07]	[0.26]	[-1.3]	[2.21]		[1.15]	
$\beta_{RET_{m-1}}$		-2.294***	-1.71***	-2.25***	-2.276***	-2.198***	-2.458***	-2.607***	-1.812***	-2.601***	-1.43
		[-3.46]	[-3.5]	[-3.57]	[-4.08]	[-4.55]	[-8.21]	[-3.25]	[-3.65]	[-3.09]	[-1.47]
$\beta_{RET_{m-12.m-2}}$		2.719***	2.489***	2.736***	3.165***	2.904***	2.374***	2.941***	2.668***	-8.081***	0.814
		[2.97]	[2.74]	[3.05]	[5.02]	[4.64]	[6.59]	[3.43]	[3.72]	[-2.78]	[0.84]
β_{ISSUE}			0.177							1.005**	0.006
			[1.05]							[2.29]	[0.06]
β_{Acc}				0.033						0.055	0.113***
				[1.38]						[1.22]	[3.2]
β_{AG}					0.024					-0.03	0.051***
					[1.15]					[-0.73]	[11.82]
β_{IVA}						-0.006				-0.302**	0.032***
						[-0.79]				[-2.45]	[14.64]
β_{IVOL}							0.018			0.055	-0.222***
							[1.6]			[0.83]	[-14.01]
β_{IO}								-0.01		0.613	0.039*
								[-0.41]		[0.83]	[1.65]
FF3 factors	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R	0.92%	3.22%	5.33%	3.28%	3.20%	3.11%	4.18%	3.09%	3.42%	3.94%	5.17%

No. obs.	334354	289300	289300	289300	289300	289300	289300	289300	289300	289300	289300

Notes: This table reports times-series average premiums of a series of variables, including stock misvaluation (MSVF), LOGME, LOGBM, stock return over a short period (RET_{m-1}), stock momentum ($RET_{m-12,m-1}$), share issuance (ISSUE), operating accruals (ACC), asset growth (AG), investment-to-asset ratio (IVA), idiosyncratic volatility (IVOL) and institutional ownership (IO). These premiums are reported by multiplying 100. Loadings of Fama-French 3 factors and industry dummies are also used as control variables to run cross-sectional regressions. The adjusted R square and the number of observations is also reported. The t-value is calculated using Newey-West standard errors with a 12-month lag. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

2.4.5. Misvaluation Factor and Misvaluation Comovement

We have shown that MSVF has predictive power for stock returns in the cross-section and the return predictive power does not disappear with increments of a variety of conventional variables. In this section, we will examine misvaluation comovement in the Chinese stock market by constructing a misvaluation factor (MSV). Compared with stock misvaluation (MSVF), which measures a firm's idiosyncratic risk, MSV measures systematic risk, as the loading on MSV proxies for systematic misvaluation. The factor loading can capture the extent to which a stock inherits misvaluation from the MSV factor.

2.4.5.1. Summary Statistics of Factor Portfolios and the Relation Among Them

Before examining misvaluation comovement, we first summarise the statistics of the factor portfolios and then test the relations among the factors, including the misvaluation factor (MSV), market factor (MKT), size factor (SMB), book-to-market factor (HML), momentum factor (MOM), liquidity factor (LIQ), investment factor (INV) and leverage factor (LEV). The detail of the factors' construction has been given in section 2.3.2.

In Table 2.7, the monthly mean returns in excess of the risk-free rate are 1.565% for $\mathrm{MSV_L^F}$, 0.997% for $\mathrm{MSV_M^F}$ and 0.525% for $\mathrm{MSV_H^F}$. MSV, which longs on $\mathrm{MSV_L^F}$ and shorts on $\mathrm{MSV_H^F}$, earns a positive mean return of 1.04% (t=3.21). In particular, the MSV has the highest Sharpe ratio among the other factors, at 0.262%. The Sharpe ratio of MSV is much higher than that of other factors.

Table 2.7. Summary statistics of factors

Panel A

Factor name	Mean return	T-value	Sharp ratio	Positive	HoldingPeriod
MKT	0.901	[1.01]	0.109	56.11%	12
SMB	0.812	[0.37]	0.146	56.11%	12
HML	0.12	[0.57]	0.036	52.22%	12
INV	-0.081	[-0.41]	-0.027	51.92%	12
LEV	-0.074	[-0.32]	-0.021	54.17%	12
LIQ	-0.273	[-0.67]	-0.048	48.28%	12
MSV	1.04***	[3.21]	0.262	63.46%	12
MSV_L^F	1.565	[1.5]	0.166	55.77%	12
MSV_M^F	0.997	[1.02]	0.112	55.77%	12
MSV_H^F	0.525	[0.53]	0.060	54.49%	12

Panel B

	MSV_L^F	MSV_M^F	MSV_H^F	MSV
				Mean
Positive	2.752**	2.226*	1.765	0.987***
	[2]	[1.75]	[1.27]	[2.62]
Negative	0.282	-0.331	-0.815	1.097**
	[0.32]	[-0.41]	[-1.09]	[2.14]
N - P				0.11***
				[17.30]

Notes: Panel A reports the summary statistics of misvaluation factor MSV and the other risk factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), investment factor (INV), liquidity factor (LIQ) and leverage factor (LEV). Stocks are sorted based on MSVF at the end of each June. MSV_L^F, MSV_M^F and MSV_H^F are portfolios including stocks within the bottom 30%, middle 40% and top 30% MSVF groups, respectively. Mean return is the average monthly return in excess of the one-month risk-free rate. Sharpe ratio is defined as the ratio of the average excess monthly return divided by the return standard deviation. Positive% is the percentage of months with positive portfolio returns. Holding period shows the number of months that we hold the factor portfolio for. Panel B reports the average monthly excess return of MSV_L^F,

MSV_M^F, MSV_H^F and MSV in the positive and negative sentiment subperiod. The positive/negative sentiment period is defined when the change of investor sentiment is positive or negative in the current month. The t-value is calculated based on Newey-West standard errors with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

We also analyse the impact of investor sentiment on stock misvaluation. The increasing investor sentiment indicates more speculative demand for investors who delate the stock misvaluation correction and, thus, decrease the MSV return. In contrast, the decreasing investor sentiment reduces speculative demands of investors and helps the misvaluation correction process, thereby increasing the MSV return. Panel B of Table 2.7 shows the MSV performance conditional on whether the current month experiences a positive or negative investor sentiment change. We find that MSV shows a positive return in both positive and negative investor sentiment changes, at 0.987 (t=2.62) and 1.097 (t=2.14), respectively. Importantly, the difference of MSV between the negative and positive sentiment change is positive and significant, at 0.11 (t=17.30). This finding confirms that investor sentiment could affect the stock misvaluation factor by affecting investors' speculative demand.

We also investigate whether MSV performance is sensitive to the length of holding periods. This investigation allows us to time the misvaluation correction. We show the performance of MSV across holding periods from 1 month to 36 months in Table 2.8. Panel A reports that the mean return and Sharpe ratio of MSV remain positive across 36 holding periods, both with downward trends. In particular, MSV return starts to become statistically insignificant in the 31st holding period. This finding reflects that returns derived from the signal of stock misvaluation only persist for a short-term and disappear over the longer period, because stock misvaluation corrects during the third holding year. Panels B and C show the MSV performance of SOEs and non-SOEs. The misvaluation of SOEs corrects a half year earlier than non-SOEs, with 31th and 38th for the mispricing correction period of SOEs and non-SOEs, respectively. The correction process can be expedited by government announcements and interventions. Investors may lack access to some information related to SOEs, until it is officially announced by government. When this hidden information is released, such as the government's commitment to maintaining the financial health of SOEs, it can be perceived by market participants, who more quickly update their opinions of SOEs than non-SOEs, causing faster misvaluation correction.

Additionally, we show the trend of MSV return and Sharp ratio across 36 holding periods in Figure 2.2. We find that the mean return and Sharp ratio of MSV decrease from a high level towards 0, reflecting that stock misvaluation is gradually corrected by the market over time.

Table 2.8. MSV performances within 36 holding periods

Panel A – Whole sample

Name	Mean return	T	Sp.	Positive %	Holding Period
MSV	2.854***	[6.34]	0.557	76.28	1
MSV	2.615***	[5.96]	0.539	74.36	2
MSV	2.547***	[5.66]	0.522	74.36	3
MSV	2.054***	[5.12]	0.428	70.51	4
MSV	2.135***	[5.1]	0.448	69.23	5
MSV	1.781***	[4.23]	0.357	67.31	6
MSV	1.794***	[4.53]	0.364	64.74	7
MSV	1.718***	[4.28]	0.378	66.03	8
MSV	1.602***	[3.56]	0.315	64.10	9
MSV	1.724***	[3.94]	0.359	64.10	10
MSV	1.418***	[3.77]	0.327	62.18	11
MSV	0.87***	[2.65]	0.219	63.46	12
MSV	1.771***	[4.34]	0.394	65.38	13
MSV	1.354***	[3.91]	0.307	62.82	14
MSV	1.126***	[3.15]	0.259	64.74	15
MSV	0.987**	[2.51]	0.216	61.54	16
MSV	1.278***	[2.71]	0.228	63.46	17
MSV	0.931**	[2.14]	0.181	58.97	18
MSV	1.242***	[3.14]	0.257	68.59	19
MSV	1.087***	[2.78]	0.233	60.90	20
MSV	1.025***	[2.99]	0.240	58.97	21
MSV	0.915***	[2.96]	0.248	58.33	22
MSV	0.839***	[2.68]	0.219	60.26	23
MSV	0.84***	[2.95]	0.233	60.26	24
MSV	0.978**	[2.54]	0.216	64.74	25

Panel B SOE subsample

Name	Mean return	T	Sp.	Positive%	Holding Period
MSV_{SOE}	2.519***	[5.76]	0.490	71.79	1
MSV_{SOE}	2.363***	[5.45]	0.479	68.59	2
MSV_{SOE}	2.252***	[5.25]	0.459	69.87	3
MSV_{SOE}	1.816***	[4.55]	0.380	69.23	4
MSV_{SOE}	1.975***	[4.54]	0.389	69.23	5
MSV_{SOE}	1.559***	[3.71]	0.305	64.74	6
MSV_{SOE}	1.485***	[4.05]	0.309	61.54	7
MSV_{SOE}	1.582***	[3.96]	0.341	65.38	8
MSV_{SOE}	1.309***	[2.91]	0.252	65.38	9
MSV_{SOE}	1.633***	[3.59]	0.323	66.03	10
MSV_{SOE}	1.309***	[3.49]	0.292	65.38	11
MSV_{SOE}	0.829**	[2.37]	0.188	60.26	12
MSV_{SOE}	1.468***	[3.82]	0.334	63.46	13
MSV_{SOE}	1.11***	[3.4]	0.262	60.26	14
MSV_{SOE}	0.9**	[2.43]	0.197	64.74	15
MSV_{SOE}	0.879**	[2.23]	0.193	61.54	16
MSV_{SOE}	1.035**	[2.29]	0.192	62.18	17
MSV_{SOE}	0.788*	[1.87]	0.155	61.54	18
MSV_{SOE}	1.02**	[2.51]	0.207	62.82	19
MSV_{SOE}	1.019***	[2.61]	0.224	60.90	20
MSV_{SOE}	0.937***	[2.93]	0.228	61.54	21
MSV_{SOE}	0.833**	[2.56]	0.209	60.26	22
MSV_{SOE}	0.727**	[2.26]	0.187	57.69	23
MSV_{SOE}	0.785***	[2.73]	0.204	57.69	24
MSV_{SOE}	0.877**	[2.28]	0.187	66.67	25

MSV	0.712**	[1.97]	0.174	60.26	26
MSV	0.787**	[2.26]	0.191	61.54	27
MSV	0.731**	[2.36]	0.190	60.90	28
MSV	0.721**	[2.28]	0.189	59.62	29
MSV	0.757**	[2.11]	0.168	58.33	30
MSV	0.573	[1.56]	0.131	55.13	31
MSV	0.446	[1.31]	0.113	57.05	32
MSV	0.496	[1.35]	0.113	55.13	33
MSV	0.605*	[1.95]	0.153	58.33	34
MSV	0.422	[1.36]	0.107	55.13	35
MSV	0.418	[1.45]	0.115	56.41	36

MSV_{SOE}	0.635*	[1.66]	0.140	58.97	26
MSV_{SOE}	0.64*	[1.69]	0.138	60.26	27
MSV_{SOE}	0.636**	[1.96]	0.148	57.69	28
MSV_{SOE}	0.649**	[2.06]	0.162	61.54	29
MSV_{SOE}	0.716*	[1.95]	0.156	59.62	30
MSV_{SOE}	0.493	[1.36]	0.111	58.97	31
MSV_{SOE}	0.367	[1.04]	0.087	57.69	32
MSV_{SOE}	0.387	[1.08]	0.089	55.77	33
MSV_{SOE}	0.424	[1.34]	0.105	57.05	34
MSV_{SOE}	0.33	[0.98]	0.077	55.13	35
MSV_{SOE}	0.331	[1.09]	0.083	57.69	36

Panel C NONSOE subsample

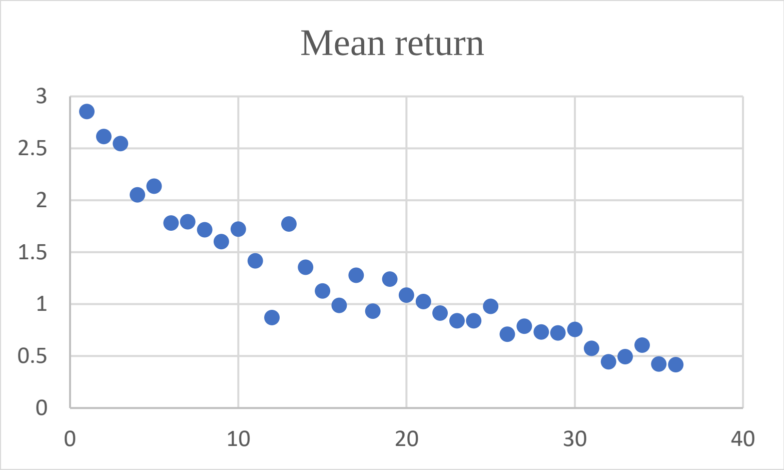
Name	Mean return	T	Sp.	Positive%	Holding Period
MSV_{NSOE}	2.455***	[4.81]	0.405	73.08	1
MSV_{NSOE}	2.289***	[4.82]	0.405	71.79	2
MSV_{NSOE}	2.195***	[4.4]	0.378	74.36	3
MSV_{NSOE}	2.066***	[4.36]	0.362	69.87	4
MSV_{NSOE}	1.65***	[3.37]	0.276	69.23	5
MSV_{NSOE}	1.82***	[4.15]	0.345	70.51	6
MSV_{NSOE}	1.737***	[3.95]	0.326	71.15	7
MSV_{NSOE}	1.444***	[3.54]	0.284	69.87	8
MSV_{NSOE}	1.648***	[3.42]	0.294	67.95	9
MSV_{NSOE}	1.492***	[3.55]	0.298	65.38	10
MSV_{NSOE}	1.2***	[2.98]	0.258	65.38	11
MSV_{NSOE}	1.035***	[2.89]	0.260	66.67	12
MSV_{NSOE}	1.567***	[3.17]	0.261	66.67	13

MSV_{NSOE}	1.316***	[2.98]	0.244	64.74	14
MSV_{NSOE}	1.226***	[2.89]	0.224	66.67	15
MSV_{NSOE}	0.831**	[2.06]	0.168	65.38	16
MSV_{NSOE}	1.382***	[3.1]	0.264	67.95	17
MSV_{NSOE}	1.268***	[2.89]	0.258	62.82	18
MSV_{NSOE}	1.229***	[3.09]	0.255	58.97	19
MSV_{NSOE}	1.074***	[2.69]	0.229	60.90	20
MSV_{NSOE}	0.993***	[2.62]	0.230	64.74	21
MSV_{NSOE}	0.813**	[2.27]	0.201	59.62	22
MSV_{NSOE}	0.821**	[2.31]	0.192	59.62	23
MSV_{NSOE}	0.877***	[2.72]	0.235	66.03	24
MSV_{NSOE}	0.969**	[2.33]	0.191	60.90	25
MSV_{NSOE}	0.823**	[2.09]	0.175	61.54	26
MSV_{NSOE}	0.882**	[2.35]	0.184	59.62	27
MSV_{NSOE}	0.806**	[2.24]	0.188	58.33	28
MSV_{NSOE}	0.857**	[2.15]	0.179	60.90	29
MSV_{NSOE}	0.875**	[2.56]	0.194	62.82	30
MSV_{NSOE}	0.787**	[2.06]	0.173	60.90	31
MSV_{NSOE}	0.737**	[2.07]	0.172	61.54	32
MSV_{NSOE}	0.794**	[2.12]	0.177	58.97	33
MSV_{NSOE}	0.998***	[2.95]	0.243	65.38	34
MSV_{NSOE}	0.772**	[2.27]	0.195	61.54	35
MSV_{NSOE}	0.718**	[2.12]	0.189	60.90	36
MSV_{NSOE}	0.629**	[2.57]	0.206	62.82	37
MSV_{NSOE}	0.607	[1.6]	0.140	57.69	38

Notes: This table shows the mean returns and Sharpe ratios of MSV across 36 holding periods. Mean return is the average monthly return in excess of the one-month risk-free rate. T is the t-value of MSV mean returns. Sharpe ratio is defined as the ratio of the average excess monthly return divided by the return standard deviation. Positive% is defined as the percentage of months with positive portfolio return (reported in percentages). Holding period is the length of months that investors hold the MSV factor portfolio.

Figure 2.2. Mean return and Sharpe ratio of MSV factor across 36 holding periods

Figure 2.2.1. Whole sample



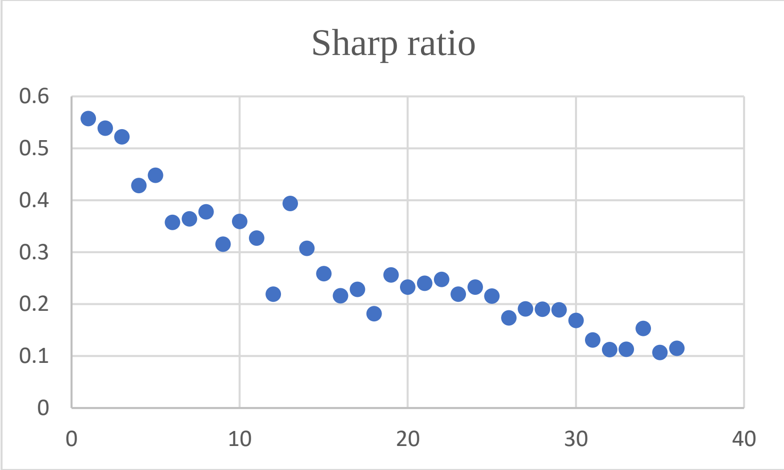
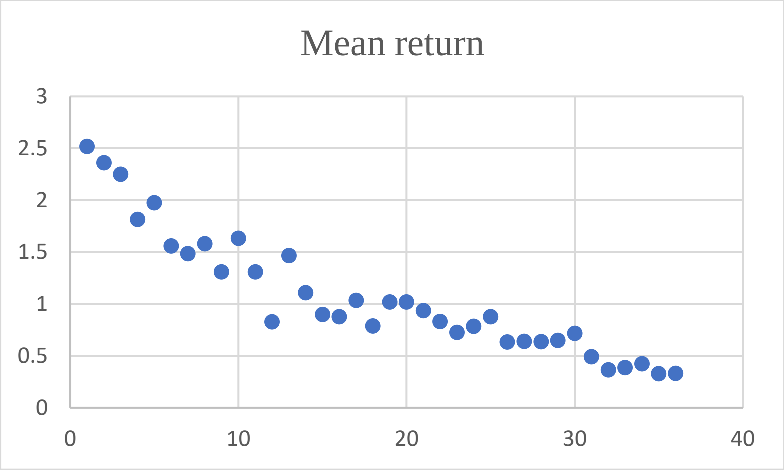


Figure 2.2.2. SOE subsample



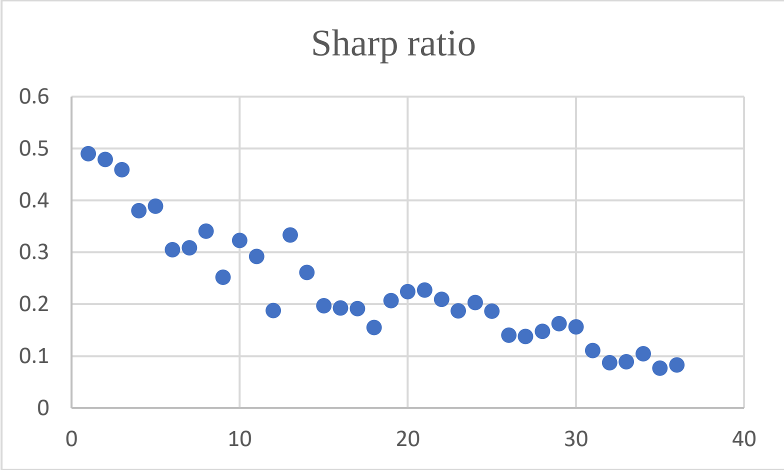


Figure 2.2.3. NONSOE subsample

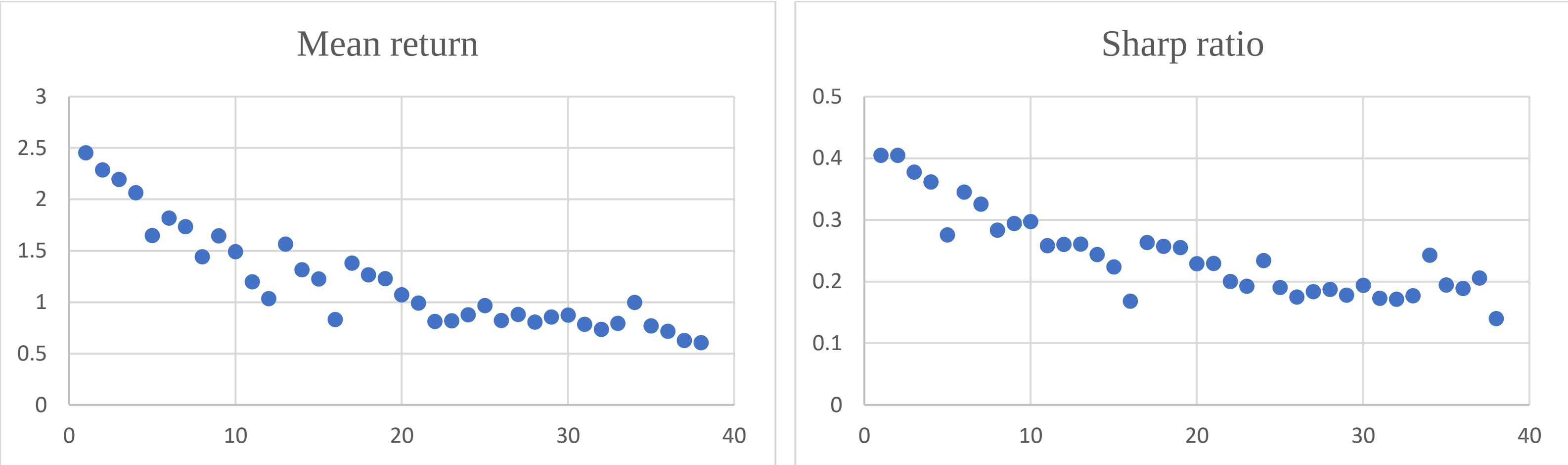


Figure 2.2.4. Mean return comparision between SOE and NONSOE

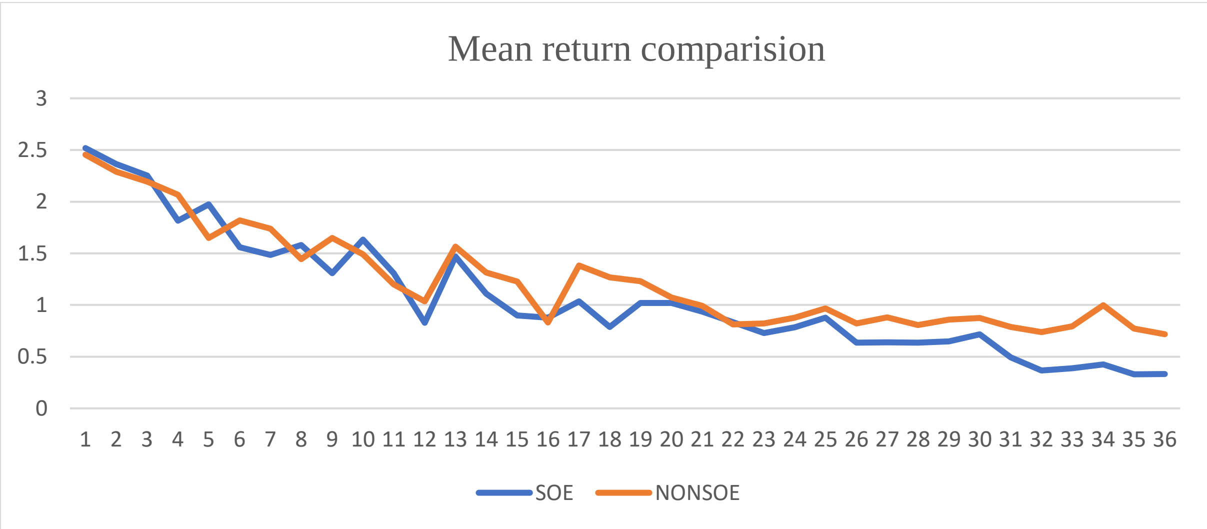


Table 2.9 reports the relation between the MSV factor and other factors. In Panel A of Table 2.9, MSV shows a weak correlation with other factors. In particular, the correlation between MSV and HML is low at -0.02. Moreover, MSV and SMB have a comparatively high correlation of 0.611.

Panel B of Table 2.9 shows the results of regressing MSV on other factors. It is important to note that all regressions reveal positive and significant intercepts, indicating that the abnormal returns of MSV are positive and, therefore, higher relative to other risk factors' return. This result is consistent with that of Table 2.7, where both the monthly return and sharp ratio of MSV are positive. Positive and significant intercepts also suggest that the misvaluation information contained in MSV cannot be fully explained by other conventional factors. In detail, the betas of the SMB and HML factors remain positive and significant across all regressions. Further, LEV is positively and significantly correlated with MSV. Their signs do not reverse and remain statistically significant in regression 6, where all risk factors are included. This finding shows that SMB, HML and LEV are correlated with MSV. In other words, they partially contribute to explaining systematic misvaluation proxied by MSV, rather than fully capturing the misvaluation information, due to significant intercepts of the regressions.

Table 2.9. Relation between MSV and other factors

Panel A Pearson correlation among factors

	MKT	SMB	HML	MOM	LIQ	INV	LEV	MSV
MKT	1							
SMB	0.106	1						
	(0.177)							
HML	-0.051	-0.538	1					
	(0.522)	(<.0001)						
MOM	-0.098	-0.505	0.402	1				
	(0.217)	(<.0001)	(<.0001)					
LIQ	-0.193	-0.822	0.551	0.399	1			
	(0.014)	(<.0001)	(<.0001)	(<.0001)				
INV	0.025	-0.251	-0.212	0.022	0.281	1		
	(0.753)	(0.002)	(0.008)	(0.781)	(0.0004)			
LEV	-0.132	-0.470	0.467	0.224	0.524	-0.014	1	
	(0.095)	(<.0001)	(<.0001)	(0.004)	(<.0001)	(0.859)		
MSV	0.059	0.611	-0.020	-0.275	-0.420	-0.317	-0.055	1
	(0.461)	(<.0001)	(0.808)	(0.001)	(<.0001)	(<.0001)	(0.495)	

Panel B Regression of MSV on other factors

	Intercept	MKT	SMB	HML	MOM	LIQ	INV	LEV	Adj.R^2	No.Obs.
1	0.003**	-0.005	0.476***	0.408***					49.50%	156
	[2.27]	[-0.14]	[7.31]	[4.63]						
2	0.003**	-0.005	0.469***	0.413***	-0.018				49.24%	156
	[2.4]	[-0.15]	[7.04]	[5.08]	[-0.4]					
3	0.003**	0	0.523***	0.391***		0.063			49.55%	156

	[2]	[0]	[6.8]	[3.86]		[0.75]				
4	0.003**	-0.004	0.471***	0.399***			-0.021		49.19%	156
	[2.28]	[-0.12]	[6.41]	[4.76]			[-0.31]			
5	0.003**	0.001	0.51***	0.355***				0.178**	51.99%	156
	[2.2]	[0.04]	[7.12]	[3.58]				[1.96]		
6	0.003**	0.004	0.522***	0.341***	-0.008	0.033	-0.026	0.168*	51.14%	156
	[2.09]	[0.09]	[7.44]	[4.15]	[-0.21]	[0.36]	[-0.27]	[1.64]		

Notes: This table reports the relationship between MSV and other factors, including market factor (MKT), size factor (SMB), book-to-market factor (HML), momentum factor (MOM), liquidity factor (LIQ), investment factor (INV) and leverage factor (LEV). Panel A shows the Pearson correlation among these factors. P-values are reported in the parentheses. Panel B shows the regression results of MSV regressed on other factors. Regression 1 only includes MKT, SMB and HML as basic independent variables. MOM, LIQ, INV and DE are added in sequence within the regressions from 2 to 5. Regression 6 contains all other factors as independent variables. The adjusted R square and the number of observations is also reported. The t-values are calculated using Newey-West standard errors with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

2.4.5.2. Misvaluation Comovement – Portfolio Level

To examine the misvaluation comovement, we use Fama-Macbeth regression to explore whether loadings of MSV can predict cross-sectional portfolio returns. The dependent variables used in these regressions are 25 size-BM portfolios. To further eliminate the concern that the return predictive power of MSV comes from traditional factors, we follow Chang et al. (2013) and construct an additional factor, named $MSV\perp$, which is orthogonalized to the Fama-French 3 factors. $MSV\perp$ is the sum of the intercept and residuals in the regression where we regress MSV on the Fama-French 3 factors. $MSV\perp$ contains information which is not explained by the Fama-French 3 factors.

There are two steps in the Fama-Macbeth regression; time series regression and cross-sectional regression. We first conduct the time series regression using a rolling window with a 60-month estimation period. These loadings on factors are used as independent variables and applied to the average portfolio returns of the next 12 months to estimate premiums of the factors in the cross-sectional regression. The result is reported in Table 2.10.

In Table 2.10, the premiums of the MSV factor are positive and statically significant at the 1% level across all regressions. In column 1, we just include Fama-French 3 factors and find the loadings on both MKT and SMB are positively and significantly related to the portfolio returns. This finding remains consistent across all regressions. After adding the MSV factor in the second regression, we find the premium of MSV is 1.552, with the t-value equalling 3.32, revealing that one standard deviation increase of misvaluation factor (1.416) would result in a 2.198% increase in portfolio returns. The sign of MSV premiums remains significantly positive, and the magnitude does not significantly change with the inclusion of the MOM, LIQ, INV and LEV factors across the columns from 3 to 6. All control factors are included in column 7. Even when controlling the other factors, the premium of MSV is still positive and statistically significant. This implies that the various factors do not subsume the return predictive power of

MSV. Further, a positive and significant premium of $MSV\perp$ confirms that loadings on MSV maintain strong predictive power for cross-sectional portfolio returns with the incremental addition of conventional factors. Hence, we can conclude that loadings on MSV can positively forecast the cross-sectional future portfolio returns.

Table 2.10. Misvaluation comovement – Portfolio level

	1	2	3	4	5	6	7	8
Intercept	-6.615***	-3.665***	-4.392***	-4.622***	-3.574***	-4.147***	-0.16	-4.82***
	[-4.3]	[-2.73]	[-3.82]	[-3.99]	[-2.7]	[-2.88]	[-0.09]	[-7.1]
β_{MSV}		1.552***	1.28***	1.172**	1.495***	1.147*	1.87***	
		[3.32]	[2.81]	[2.41]	[2.65]	[1.91]	[2.58]	
$\beta_{MSV^{\perp}}$								0.667**
								[2.14]
β_{MKT}	5.384***	2.727**	3.813***	3.945***	2.673**	3.517***	0.032	4.366***
	[3.31]	[2.18]	[3.84]	[4.03]	[2.14]	[2.98]	[0.02]	[6.24]
β_{SMB}	1.889**	1.739**	1.44*	1.628*	1.646**	1.49*	0.734	1.457***
	[2.26]	[2.18]	[1.91]	[1.95]	[2.16]	[1.9]	[1.16]	[2.6]
β_{HML}	-0.032	-0.788**	-0.831**	-0.708*	-0.871**	-0.854**	-0.594**	-0.737**
	[-0.07]	[-2.23]	[-2.29]	[-1.83]	[-2.45]	[-2.42]	[-2.45]	[-2.52]
β_{MOM}			1.914				0.293	0.326
			[1.58]				[0.33]	[0.72]
β_{LIQ}				-0.507			-0.059	-0.025
				[-0.59]			[-0.63]	[-0.44]
β_{INV}					0.229		-0.211	0.555*
					[0.49]		[-0.47]	[1.84]
β_{LEV}						0.266	0.502	-0.325
						[0.44]	[1.06]	[-0.63]
Adj. R^2 (%)	45.45%	54.23%	56.30%	57.61%	55.57%	56.62%	56.72%	61.10%
No. obs.	3900	3900	3900	3900	3900	3900	3900	3900

Notes: This table shows the time-series average of premiums of the misvaluation factor (MSV) and other factors, including the orthogonalized MSV factor ($MSV^{\perp}$), market factor (MKT), size factor (SMB), book-to-market factor (HML), momentum factor (MOM), liquidity factor (LIQ), investment factor (INV) and leverage factor (LEV), based on the Fama-Macbeth regression. These factors are regressed on the monthly value-weight excess return of 25 portfolios, which are formed on the intersection of size and book-to-market quintiles. The adjusted R square and number of observations of each regression are reported at the bottom of the table. The t-value is calculated using Newey-West standard errors, with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

2.4.5.3. Misvaluation Comovement – Stock Level

So far, we have examined the misvaluation comovement from the portfolio level and find loadings of MSV are positively related to portfolio returns in the cross-section. In this section, we move to the stock-level analysis. We expect that the return predictive power from loadings of MSV can also be found in the cross-sectional stock return. Compared with the portfolio-level analysis, the estimated loadings on individual stock returns are more unstable. To alleviate the estimation noise, we follow Chang et al. (2013) and use two methods to estimate loadings on MSV.

In the first method, we regress the daily excess stock return on the market factor (MKT), size factor (SMB), book-to-market factor (HML) and misvaluation factor (MSV). This regression is conducted using a monthly rolling window with a 12-month estimation period, where the number of observations is greater than 100. The regression equation is:

$$Ret_{i,t} = \beta0_{i,t} + \beta1_{i,t}MKT_{i,t} + \beta2_{i,t}SMB_{i,t} + \beta3_{i,t}SML_{i,t} + \beta4_{i,t}MSV_{i,t} + \epsilon_{i,t} \qquad (2.4)$$

We target the beta of MSV, denoted as β_{MSV}. Stocks are sorted into deciles, based on β_{MSV}. The time-series average of each decile return is calculated, as well as MSVF, ME, BM and MOM across β_{MSV} deciles, and reported in Table 2.11.

In Table 2.11, β_{MSV} increases monotonously across deciles, from low to high. The average β_{MSV} for the bottom and top deciles are -2.327 and 1.792, respectively. In contrast, MSVF shows a decreasing trend across deciles. This result confirms that stocks with negative β_{MSV} are systematically overvalued, while stocks with positive β_{MSV} are systematically undervalued. Importantly, decile returns increase across deciles. The difference between high and low deciles generates a significant positive return, which is 1.365% and significant at the

1% level (t=3.12). After adjusting by the market factor (CAPM), Fama-French 3 factor (FF3) and 4 factors (FF3+MOM), abnormal returns on these regressions remain positive and significant, at 1.231 (t=3.11), 1.012 (t=2.56) and 0.952 (t=2.38), respectively. These findings reveal that significant profits can be earned by going long in undervalued deciles and selling overvalued deciles, based on the return predictive information of β_{MSV}. Conventional factors do not subsume the return predictive power of β_{MSV}.

The last three columns show the characteristics of ME, BM and MOM for each decile. ME increases from the low to middle deciles and then decreases with increasing deciles. The lowest ME occurs on the high decile, which is 8,739 million. This figure is obviously lower than for the low decile, with the difference of -3,325 million, revealing that stocks with high β_{MSV} are smaller in size and tend to be undervalued. BM shows an increasing trend from low decile to high decile. This result reveals that stocks with high β_{MSV} are more likely to be undervalued, and vice versa. However, MOM shows a downward trend along deciles, even if the decreasing trend is not monotonous, indicating that stocks with good (poor) performance tend to be overvalued (undervalued).

Table 2.11. Deciles sorted on β_{MSV}

	β_{MSV} Rank	β_{MSV}	Ret (%)	MSVF	ME (million)	BM	MOM
	L	-2.327	-0.761	0.388	12298	0.873	2.414
	2	-1.294	0.084	0.286	12617	0.880	1.394
	3	-0.866	0.627	0.227	12915	0.884	0.930
	4	-0.553	0.552	0.154	13266	0.889	0.501
	5	-0.292	0.751	0.091	13869	0.893	0.298
	6	-0.055	0.961	0.019	15725	0.897	0.413
	7	0.189	0.907	-0.047	17854	0.901	0.138
	8	0.469	0.871	-0.097	15856	0.905	0.113
	9	0.856	1.255	-0.214	13678	0.911	0.287
	H	1.792	1.857	-0.632	8739	0.936	0.168
	H-L	4.076***	1.365***	-1.06***	-3325**	0.065***	-2.064**
		[66.22]	[3.12]	[-12]	[-2.44]	[9.46]	[-2.06]
CAPM α	1.231***						
	[3.11]						
FF3 α	1.012**						
	[2.56]						
FF3 +MOM α	0.952**						
	[2.38]						

Notes: This table reports monthly decile returns, based on the sort of β_{MSV}, which is estimated by regressing the individual stock return on the MSV factor, controlling the Fama-French 3 factors. The average MSVF, market capitalisation (ME) in millions, book-to-market ratio (BM), and momentum (MOM) are also reported in this table. The rows H-L highlight the differences between top and bottom deciles. In addition, return differences between the top and bottom decile returns are adjusted by, respectively, the market factor (CAPM), Fama-French 3 factors (FF3) and Fama-French 3 factors plus the Momentum factor (FF3 +MOM). The abnormal returns of these three regressions are also reported. The t-value is calculated using the Newey-West standard error, with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

Although the first method can estimate the loadings of MSV in stock-level, the estimation of loadings is not precise enough, because stock-level loadings are more subject to regression to the mean. To improve the precision of estimation on β_{MSV}, we follow Chang et al. (2013) and use the second method to estimate loadings from characteristics portfolios. In fact, this method is a modified version of the portfolio shrinkage method, which is used as the estimation procedure in Fama and French (1993). Instead of using the past three-year to five-year stock returns, we use annually balanced portfolios sorted by size and MSVF.

In the second method, we use characteristics portfolios as dependent variables to estimate the loading of MSV in the time-series regression over the past 36 months. To form characteristics portfolios, we use size to sort stocks into deciles and then use MSVF to sort into deciles within each size decile, to form 100 portfolios[7] at the end of each June. We further assign loadings on MSV to individual stocks, which are included in the portfolio, in the cross-sectional regression. Individual stock returns are regressed on loadings of MSV and various firm-level variables, including LOGME, LOGBM, Ret_{m-1}, $Ret_{m-1,m-12}$, ISSUE, ACC, AG, IVA and DE, to alleviate the concern that the effect of MSV's loading is not solely driven by stock exposures to firms' idiosyncratic risk. We also control the betas of a set of market-wide risk factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), momentum factor (MOM), liquidity factor (LIQ), investment factor (INV) and leverage factor (LEV). These results are shown in Table 2.12.

In Table 2.12, premiums of MSV remain positive and statistically significant across all regressions, indicating that MSV contains predictive power for cross-sectional stock returns. This result is consistent with that of Table 2.10, which examines the misvaluation comovement at the portfolio level.

[7] Note: These 100 size-MSVF portfolios are not the same as the 100 size-BM portfolios formed in Table 2.6.

Table 2.12. Misvaluation comovement – stock level

	1	2	3	4	5	6	7	8	9
Intercept	1.716	-0.935	-39.762***	1.265	1.433	1.6	2.275	-34.647***	-35.045***
	[0.26]	[-0.14]	[-6.11]	[0.17]	[0.19]	[0.21]	[0.35]	[-4.38]	[-4.53]
β_{MSV}	2.231***	2.356***	2.496***	3.696***	3.701***	3.703***	2.417***	3.545***	
	[9.17]	[10.11]	[9.33]	[9.02]	[9.03]	[12.31]	[8.02]	[9.46]	
$\beta_{MSV^{\perp}}$									1.019***
									[5.2]
LOGME	0.866***	0.972***	3.801***	1.767***	1.757***	1.766***	0.961***	3.881***	3.881***
	[4.41]	[5.12]	[12.5]	[6.72]	[6.78]	[6.76]	[5.03]	[15.96]	[9.28]
LOGBM	-20.682***	-20.506***	25.758***	-46.375***	-46.36***	-46.702***	-23.985***	-0.055	0.317
	[-6.4]	[-5.97]	[4.19]	[-9.83]	[-9.78]	[-9.87]	[-6.61]	[-0.24]	[0.03]
Ret_{m-1}		-3.971***	-4.881***	-5.247***	-5.29***	-5.27***	-4.053***	-5.951***	-5.941***
		[-3.49]	[-4.31]	[-4.55]	[-4.62]	[-4.57]	[-3.54]	[-22.8]	[-5.19]
$Ret_{m-12,m-1}$		-2.855***	-3.042***	-3.109***	-3.123***	-3.114***	-2.862***	-3.266***	-3.25***
		[-2.99]	[-3.14]	[-3.33]	[-3.36]	[-3.35]	[-3]	[-13.45]	[-3.52]
ISSUE			-3.334***					-2.627***	-2.626***
			[-9.59]					[-6.23]	[-4.21]
ACC				0.011				0.016	0.017
				[0.58]				[0]	[1.03]
AG					1.05			1.765	1.773
					[0.99]			[1.55]	[1.12]
IVA						-0.364		-0.953	-0.985**
						[-0.88]		[-1.03]	[-2.09]
DE							0.026***	-0.045	-0.046**
							[4.33]	[-0.07]	[-2.49]
Risk factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Ind. Dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	3.19%	5.54%	6.86%	6.66%	6.72%	6.67%	5.59%	7.92%	7.90%
No. obs.	187128	187128	187128	178744	178744	178744	187128	178744	178744

Notes: This table reports the Fama-Macbeth regression of individual stock returns on loadings of the misvaluation factor (MSV). MSV is regressed on monthly value-weight excess returns of 100 portfolios, which are formed on size and MSVF deciles, over the past 36 months. Factor loadings estimated in the previous step are applied to individual stocks included in the portfolio over the next month. To estimate the premium of MSV, we control a set of variables, including LOGME, LOGBM, Ret_{m-1} , $\mathrm{Ret}_{m-12,m-1}$, ISSUE, ACC, AG, IVA, DE and $\mathrm{MSV}^{\mathrm{F}}$. We also control the betas of a set of risk factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), momentum factor (MOM), liquidity factor (LIQ), investment factor (INV) and leverage factor (LEV). Industry dummies are included as control variables in each regression. The adjusted R square and number of observations of each regression are reported at the bottom of the table. The t-value is calculated using Newey-West standard errors, with a 12-month lag and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels, respectively.

In the first regression, we estimate the premium of MSV, controlling LOGME and LOGBM. We find that the premium of MSV is positive and significant, at 2.231 (t=9.17). This result indicates that one standard deviation increase of the misvaluation factor (1.42) would result in a 3.168% increase in portfolio returns. In the second regression, we also take Ret_{m-1} and $Ret_{m-1,m-12}$ into the regressions. Controlling these four variables, the premium of MSV remains positive and statistically significant. Besides this, LOGME is positively and significantly related to stock returns, while LOGBM, Ret_{m-1} and $Ret_{m-1,m-12}$ are negatively and significantly related to stock returns. The premium sign of MSV and the beta signs of these control variables do not reverse after adding ISSUE, ACC, AG, IVA and DE in sequence into the regressions from 3 to 7. In regression 8, we include all firm variables and find these control variables do not subsume the return predictive information of MSV. Further, we construct an orthogonalized misvaluation factor ($MSV\perp$) in the last regression to filter out possible information of MSV subsumed by the Fama-French 3 factors, and find that the premiums on $MSV\perp$ are still positive and significant.

2.5. Conclusion

In this chapter, we use a misvaluation measure and a misvaluation factor to examine their return predictive power. There are three main findings. Firstly, we modify the pricing deviation-based approach of Rhodes–Kropf et al. (2005) and Chang et al. (2013), by adding ownership classification, to estimate firm value and create the misvaluation measure for each firm. The misvaluation measure caters to the characteristics of Chinese firms. We find loadings on stock misvaluation (MSVF) can negatively predict future China A-share stock returns beyond various conventional firm variables, implying that stock misvaluation corrects over time. Interesting, we find the difference between the bottom and top MSVF deciles yields more returns for SOEs than non-SOEs, reflecting that the SOE misvaluation effect is stronger. Second, we construct a misvaluation factor (MSV) and time the misvaluation correction, finding that the stock misvaluation of SOEs corrects faster than that of non-SOEs. This finding implies that investors may exaggerate the information asymmetry of SOEs, worsening the misvaluation. They revaluate more efficiently when hidden information is released. Third, we examine misvaluation comovement on both portfolio- and stock-level analyses. We find that the MSV factor has strong predictive power for both portfolio and stock returns. Loadings on MSV can positively and significantly forecast the future cross-section returns on portfolios and stocks. In summary, we find a misvaluation effect exists in the Chinese stock market and this effect is stronger than in the US stock market.

GRADUATE RESEARCH SCHOOL

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Student name:	Qifang Feng
Name and title of main supervisor:	Professor Xiaoming Li
In which chapter is the manuscript/published work?	Chapter Three

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]

Qifang is the main author of this essay, and while his supervisors have made substantial contributions, reflected through co-authorship. The essay is essentially the work of Qifang. He gathered the data, ran regressions to get the results, and wrote the paper. The supervisors contribute to the essay by providing research direction, critical comments, insightful advice, and essay revision.

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Chapter three (the second essay), "The Impact of the Imbalanced Trades between Margin Trading and Short Selling on Stock Misvaluation: Evidence from the Chinese Pilot Program", was accepted to be presented at the 28th New Zealand Finance Colloquium 2024, The University of Auckland, New Zealand.

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CHAPTER THREE

The Impact of the Imbalanced Trades between Margin Trading and Short Selling on Stock Misvaluation: Evidence from the Chinese Pilot Programme

ESSAY TWO

This chapter presents the second essay, which investigates the influence of imbalanced trading of margin traders and short sellers on stock misvaluation in the Chinese stock market. The chapter is organised as follows. Section 3.1 introduces the motivation and key findings. Section 3.2 reviews the literature. Section 3.3 presents the background of the Chinese pilot programme. Section 3.4 outlines the methodology and data sample details. Section 3.5 shows the main results and the related analysis. Section 3.6 presents the robustness check. Section 3.7 concludes the second essay. An appendix and reference list for this chapter are shown at the end of this thesis.

3.1. Introduction

The Chinese stock market starts allowing margin trading and short selling in March 2010. A pioneering study by Chang et al. (2014) shows that intensified short-selling activities, not margin-trading activities, improve price efficiency after the ban is lifted. However, their finding is subject to the limitation of the short sample period ending in December 2012. Since then, the trading volumes of margin traders and short sellers have become increasingly imbalanced due to the soaring margin-trading activities and limited securities lending. Given this evolved landscape, we first replicate the event study of Chang et al. (2014), extending the data sample period to the end of 2020. In contrast to Chang et al. (2014), we find a significant positive abnormal return on the day when the restriction on short selling and margin trading is lifted. This result suggests that excessive positive information has been incorporated into stock prices through intensified margin-trading activities, which dominate the total trading volume of the Chinese pilot programme. Motivated by the imbalanced development between margin-trading and short-selling activities and the distinct findings associated with this, this essay goes further to investigate whether and how the imbalanced trading activities between margin traders and short sellers affect price efficiency and how each influences stock misvaluation.

In the efficient market hypothesis (EMH) framework, market participants are rational, and the marketplace is frictionless. Assets are fairly valued, as their prices fully reflect all available information in the market and instantaneously respond to new information. This theory is challenged by various constraints and frictions in the market, as well as behavioural finance studies documenting how investors with heterogeneous opinions cause the financial market to operate inefficiently. Mispricing caused by behaviour biases and cognitive errors is the focus of another stream of literature that is beyond the scope of this research (for example, De Long et al. (1990) and Daniel et al. (2001)). We focus on the impact of market constraints on price efficiency.

Margin trades and short sales are commonly forbidden by regulatory authorities to maintain the stability of the stock market. The effect of margin trading and short selling on asset valuation is highly controversial, with regulations and constraints varying widely across capital markets and countries. Most studies concentrate on the effect of short-sales prohibitions on price efficiency. A short sale involves investors borrowing financial securities and immediately selling them at a comparatively high market price, with the anticipation of repurchasing them at a lower price in the future to make profits. Short-sale constraints prevent pessimistic investors from expressing negative opinions and cause stock overvaluation (Miller,1977). In a market with short-sale constraints, stock prices react slower to negative information than positive information (Diamond & Verrecchia, 1987). This view is supported by empirical evidence that short-selling constraints hinder price discovery and increase stock crash risk (Hong & Stein, 2003; Bris et al., 2007; Chang et al., 2007).

Unlike short sellers who profit from downward price movement, margin traders aim to increase profits through leverage by betting on raising prices. Margin trading allows investors to take leveraged long positions in security trading accounts with margin requirements. However, high margin requirements can restrict access to capital. Different from constraints on short sales, the ban on margin trading cannot prevent investors from exploiting positive information in the market. Optimistic investors with positive outlooks on the economy can finance capital from various sources to purchase financial securities. For example, they can establish a leveraged long position using mortgages. The impact of margin trading on stock valuation is controversial. On the one hand, the literature blames margin trading for destabilising the stock market by amplifying the noise-trading of uninformed investors (Chowdhry & Nanda, 1998; Rytchkov, 2014). On the other hand, margin trading enhances liquidity and increases information flow (Seguin, 1990).

The Chinese government lifted the ban on margin trading and short selling in March 2010 to increase stock price information efficiency. Since then, the pilot programme has undergone seven expansions[8], and the number of eligible stocks increased from 90 to 2,200 by the latest expansion. The development of margin trading and short selling has become increasingly unbalanced in the last decade, with 92%[9] of the trading volume coming from margin traders. This imbalance can be attributed to two primary factors. Firstly, Chinese investors have become accustomed to a habitual "buy" mindset, while short selling is still relatively new to them. Most of these investors are unsophisticated investors and may choose to avoid short selling. Secondly, securities lending sources are limited, as investors mainly borrow securities from a restricted pool of securities agents. The large trading volume gap between margin trading and short selling captures de facto a gap between demand and supply in the stock market and so may drive stock prices away from their fundamental values. This gap implies that more positive information is incorporated into stock prices than negative information, potentially reducing market efficiency during the pilot trading period.

Evidence from the Chinese stock market shows that the relaxation of constraints on margin trading and short selling benefits price efficiency (Chang et al., 2014). Specially, short sellers who are informed and sophisticated traders can exploit profitable opportunities (Feng & Chan, 2016). However, the improved price efficiency can be attributed to short sales rather than margin trades. For example, Chang et al. (2014) do not find evidence that margin-trading activities improve price efficiency. On the contrary, they advocate that enhanced price efficiency arises from negative information incorporated into stock prices through short-selling activities only. Although previous studies have documented the impact of short-sales in the

[8] The latest stock expansion happened on 21 Oct 2022. The Shanghai and Shenzhen stock exchanges irregularly pick up and drop off stocks after expansions. The number of eligible stocks varies between two consecutive expansions.
[9] This figure is reported based on 31 Dec 2020, the end of our data sample. The time-series trading volume comparison between margin trading and short selling is shown in Figure 3.3.

Chinese stock market, margin-trading has not yet received sufficient attention from researchers. This is despite the fact that the trading volume of margin traders has soared over the last decade, increasingly impacting the stock market, which has been notably neglected or underestimated in existing literature. In view of this, we conceive a two-stage research strategy. In the first stage, we replicate the event study of Chang et al. (2014) by extending their sample period by eight years, ending December 2020. In the extended eight years, imbalanced trades between margin-trading and short-selling activities increased dramatically relative to the first two years, as studied by Chang et al. (2014). As a result, we find, in contrast with the negative abnormal returns documented in Chang et al. (2014), positive abnormal returns on the event days when the margin-trading and short-selling bans were lifted. This suggests that stock prices are driven upwards by positive information through margin-trading activities.

Motivated by the imbalanced development between margin-trading and short-selling activities and our discovery distinct from Chang et al. (2014), we examine whether the imbalanced trading activities affect price efficiency, and how margin trades and short sales interact with each other to affect stock misvaluation. We construct a margin trading – short selling (MS) index[10], based on the short-selling ratio of Li et al. (2018), as the difference between margin-trading and short-sales amount balance scaled by tradable market shares. Compared with the short-selling ratio of Li et al. (2018), which only measures a relative value, our index could capture the trading scale and, therefore, measures the trading dispersion between margin-trading and short-selling activities for one stock in the same trading period. The higher the MS index, the larger the margin trading and short selling dispersion, and vice versa. We compare the cross-sectional average of the MS index around event trading days

[10] The detailed construction of MS index is shown in Section 3.4.1.

between the data period (P1) of Chang et al. (2014) and our extended data period (P2). The comparison demonstrates the average MS index of P2 is much higher than that of P1.

The second stage of this study also finds that the trading volume imbalance between margin-trading and short-selling activities has a significantly positive relation with stock misvaluation. More specifically, a larger difference between margin-trading and short-selling activities drives the market value of a firm further away from its estimated intrinsic value. The stock misvaluation measure (dependent variable) allows us to examine the effect of $\mathrm{MS^{DM}}$ index[11] on overvaluation and undervaluation separately. When dividing firms into over- and undervalued groups, the trading imbalance leads to escalated overvaluation in the former group and reduced undervaluation in the latter group. Furthermore, the relationship between the $\mathrm{MS^{DM}}$ index and stock misvaluation seems to have become mitigated in recent years when the Chinese government made a series of revisions to the pilot rules to constrain margin-trading and short-selling activities.

In addition, the effect of the imbalanced trading mainly derives from margin traders, whose trading volumes are positively related to the stock misvaluation measure. On the one hand, the soaring trading volume of Chinese margin traders drives up overvaluation for overvalued stocks and, therefore, decreases price efficiency. On the other hand, it also contributes to enhancing price efficiency by correcting undervaluation for undervalued stocks. This finding is different from that of Chang et al. (2014), who document that margin traders are not information providers. Furthermore, our evidence of short-selling activities is consistent with the literature. That is, short-selling activities contribute to decreasing stock misvaluation and, thus, improve price efficiency.

[11] $\mathrm{MS^{DM}}$ is the demeaned MS index. We use the demeaned MS index in regression analysis in this chapter. The construction of $\mathrm{MS^{DM}}$ is shown in Section 3.4.1.

To address the endogeneity concern, we apply two-stage least squares regression with industry means of the primary explanatory variable as the instrumental variable, and the dynamic panel generalised method of moments estimation for the robustness checks. Positive and significant parameters obtained from these two methods confirm the uncovered relationship between unbalanced trades and stock misvaluation.

The available stock-level pilot trading data allows us to investigate the imbalanced trading effect of margin-trading and short-selling activities on stock misvaluation. To the best of our knowledge, we are the first to investigate the trading imbalance issue for stock misvaluation. Our findings extend the work of Chang et al. (2014) who investigate the effect of lifting the margin-trading and short-selling ban on price efficiency. We argue that although lifting the short-sale ban enables more negative information to be incorporated into stock prices and thus enriches the information content of the stock price, the margin-trading and short-selling activities, if imbalanced, jointly drive prices away from their intrinsic values. In particular, margin-trading activities play a dominant role in affecting stock misvaluation in the Chinese stock market.

3.2. Literature Review

3.2.1. Short Sales and Price Efficiency

Miller (1977) seeds the theory that short-sale constraints create a divergence between asset prices and fundamental values. He points out that in the presence of short-sale constraints, more optimistic information could be incorporated into security prices than the average opinion of market participants and, thus, these constraints tend to make prices upward biased. The underlying nature is that pessimistic investors are driven out of the market when they face short-sale constraints and, thus, negative opinions cannot be reflected in market prices, enabling optimistic traders to bid prices above the average level which most investors recognise as fair. His theory is supported by Jarrow (1980) and Figlewski (1981), who are among the first to use the asset pricing model to test Miller's view and find results consistent with his proposition.

Diamond and Verrecchia (1987) show an alternative opinion by modelling the effect of short-sale constraints in the efficient-market framework, introducing an assumption in which risk-neutral market makers can update information between two continuous trades. In contrast to Miller (1977), they argue that prices of stocks prohibited by short sales adjust slower to negative information than to positive information. On average, there is no overvaluation existing in the market. Informed traders in this efficient environment will perceive the existence of short-sale constraints and adjust their beliefs, even though these perceptions of investors eliminate some informative trades.

Bris et al. (2007) provide international evidence that security prices reflect negative information more efficiently when short sales are allowed by comparing 46 equity markets. While measuring short-sale constraints in the cross-country framework, they cannot directly conduct overvaluation tests. They examine how short sales constraints are associated with cross-sectional variation of stock returns based on the underlying assumption that efficient price discovery causes less price comovement and higher idiosyncratic risk. Chang et al. (2007) complement the study of Bris et al. (2007) by offering a direct analysis of short-sale constraints. They document that short-sale constraints result in stock overvaluation, especially as the valuation effect becomes more significant when the dispersion of investor opinion becomes wider.

Most research cited above highlights that the short-sale constraint tends to hinder investors from exploiting negative information existing in markets. However, short sales bans might have some positive effects on the market. Short-sale constraints can play a stabilisation role in some countries where short selling is prohibited (Bris et al., 2007). His finding is supported by Chang et al. (2007), who find higher volatility and lower skewness when short selling is allowed in Hong Kong. In contrast, Hong and Stein (2003) argue that in the presence of short-sale constraints, unfavourable information tends to be hidden by investors until markets drop when this accumulated information comes out, leading to negatively skewed returns and stock crash disasters.

3.2.2. Margin Trading and Price Efficiency

Empirical findings about the effect of margin trading on asset pricing are controversial. Some studies label margin traders as speculators who destabilising the market, and document that margin trading increases the volatility associated with noise trading (Chowdhry & Nanda, 1998; Rytchkov, 2014). In other words, the leverage ability of noise traders has been enhanced when margin trading is allowed. To some extent, allowing margin trading amplifies the noise trading of uninformed investors. Moreover, Lv and Wu (2020) document that margin trading improves the price adjustment speed but decreases the information content. In contrast, Seguin (1990) shows that margin trading increases information flow and enhances depth. Margin trading also benefits liquidity during ordinary market periods, while short selling disrupts liquidity. That effect reverses when the market declines. Consistently, Chordia et al. (2001) and Alexander et al. (2004) show that allowing margin trading improves stock demand, stock market liquidity and price efficiency.

Most studies of margin trading focus on developed markets, while the Chinese stock markets show little empirical evidence that margin-trading activities contribute to price efficiency. Traditional research finds international evidence that margin trading leads to excess volatility and market destabilisation (Seguin & Jarrell, 1993; Hardouvelis & Theodossiou, 2002; Thurner et al., 2012). The ambiguous effect of margin trading on price efficiency is first pointed out by Chang et al. (2014), who show that Chinese price efficiency is improved by short-selling, not margin--trading activities. They pointed out a possible issue of the imbalanced developing trend between margin-trading and short-selling activities due to the accessibility of "refinance" and "security refinance" schemes in the Chinese equity market. Moreover, Li et al. (2018) find that margin buyers can significantly affect the return predictive power of conventional short-sales measures in the Chinese stock market. However, the short sale measure they proposed cannot capture the deviation between margin trading and short selling. In addition, Lv and Wu (2020) find that margin trading volatility decreases the information content of stock prices, and stocks with higher margin buying volatility are more likely to be overpriced in the Chinese stock markets. Their results imply that Chinese margin traders are more likely to react actively, or overreact, to good news. The margin-trading activities which incorporate a higher uncertainty of news would increase arbitrage risk, thus reducing arbitragers' activities to drive the stock price back to its intrinsic value.

3.2.3. Chinese Pilot Programme and Price Efficiency

The effect of margin trading and short selling on asset pricing is subject to the regulations of countries. The Chinese stock market relaxed the ban on margin trading and short selling on March 31, 2010. Studies find that lifting the ban on margin trading and short selling in Chinese equity markets improves price efficiency, through incorporating more negative information into stock prices (Chang et al., 2014; Chen et al., 2016; Liu et al., 2020). Chang et al. (2014) show that the cross-sectional average of abnormal returns is negative around event trading days when stocks are added to the designated list and, thus, can be bought on leverage and sold short. A higher beta and lower R square from the OLS market model associated with the pre- and post-event estimation window shows that the short-sale activity contributes to high price efficiency. They also find that trades of short sellers have return predictive power for future returns. In contrast, trades from margin traders do not show future return predictability, and these intensified margin trades are associated with lower contemporaneous returns. Chang et al. (2014) find no evidence of arbitrage from margin traders against undervaluation, implying that the trading activities of Chinese margin traders may fail to transfer market information into stock prices.

The development of margin trading and short sales is highly unbalanced over the past ten years in China, with the majority of the total trading volume dominated by margin traders. This change of development is missing in the early study of Chang et al. (2014) due to the short sample period ending in 2012. In the presence of a severe trading imbalance between margin trading and short selling, the huge trading volume of margin trading may deteriorate price efficiency by incorporating excess positive information into stock prices. However, most studies about margin trading and short selling examine either the effect of lifting the ban on margin trades or short sales on price discovery, not both. Our main purpose is to focus on the combined effect of margin trading and short sales on stock misvaluation. Another motivation for investigating the Chinese pilot programme is that the Chinese stock market is dominated by individual traders (Li & Wang, 2010; Yu et al., 2019). The composition structure of market participants may make the effect of the Chinese pilot programme on price efficiency different from that in developed markets. These individual traders are subject to psychological biases (Barber et al., 2009). Hence, noise trading of these investors would be amplified by margin trading and short selling, ultimately worsening stock misvaluation.

3.3. Chinese Pilot Programme

As mentioned above, Chinese stock markets relaxed the ban on margin trading and short selling on March 31, 2010. Since then, the Shanghai and Shenzhen stock markets started allowing qualified investors[12] to take leveraged long positions and sell short eligible stocks listed in the pilot scheme. The main purpose of the China Securities Regulatory Commission (CSRC) was to foster opposite-direction trading mechanisms, enabling positive and negative information to be incorporated into stock prices. The pilot programme starts picking 90 A-shares from the components of the SSE 50 index and the SZSE index. The number of eligible stocks has increased to 2,014 after experiencing seven expansions[13] by 31 December 2020. The number of eligible stocks occupies half of the listed shares, and the total market capitalisation of eligible stocks was more than 80% of all tradable shares. Stocks are allowed for margin trading and sell shorting when their firm characteristics, such as market value, volatility, and earnings, meet the requirements[14] of CSRC. The Shanghai and Shenzhen stock markets also infrequently delist stocks which fail to meet those requirements or cause significant illegality issues. In addition, China charges the interest fees of margin trading of 7% to 9%. This fee is comparatively high, as the US market charges an interest rate[15] of 2% to 3%.

The development of margin trading and short selling is highly unbalanced over the past ten years in China. The large difference in trading volume between margin trading and short selling might drive stock prices away from fundamentals. This issue may be against the goal

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[12] Qualified investors are those who have investment knowledge and historical trading records, with a maintenance capital of 500,000 Chinese Yuan minimum in their trading accounts, etc.

[13] Chinese stock markets experienced seven times the expansion (including the initial issuance) of eligible stocks for margin trading and short selling before the end of our data sample. The number of stocks for each time is shown as follows: 1. 90 stocks as of 31 March 2010; 2. 285 stocks as of 5 December 2011; 3. 500 stocks as of 31 January 2013; 4. 700 stocks as of 16 September 2013; 5. 900 stocks as of 22 September 2014; 6. 950 stocks as of 12 December 2016; and 7. 1600 stocks as of 19 August 2019. The latest expansion increases the number of eligible stocks from 1600 to 2200 as of 21 October 2022. Except for the expansion period, the Shanghai and Shenzhen stock markets irregularly update the eligible stocks by listing or delisting them in a small range of numbers.

[14] Eligible stocks are "blue chip" stocks with large market capitalisation, low volatility, and stable earnings performance. In the process of stock expansion, eligible firms should also meet the requirements of completing the share split reform and having shareholders numbering more than 4,000. To ensure market transparency, security firms are required to disclose trading information related to short selling and margin buying on a daily basis before 9:00 a.m. on the next trading day (T+1).
http://www.sse.com.cn/lawandrules/sselawsrules/trade/specific/margin/c/c_20210128_5312109.shtml

[15] Chinese stock markets charge the interest rate for short sellers varies from 8% to 10.5%. The changes of the interest cost are evaluated based on the qualifications of investors and financial agents. The interest fee may vary across different brokerage firms.

of the Chinese pilot programme to improve price efficiency by incorporating both optimistic and pessimistic views of investors into stock prices. Moreover, the composition structure of the market participants in the Chinese pilot programme is different from that of developed markets, such as the US. The Chinese market is dominated by individual investors who account for over 80% of market trading (Li & Wang, 2010; Yu et al., 2019). For the Chinese pilot programme, about 99% of open trading accounts[16] of Chinese margin traders and short sellers are owned by retail investors.

To increase margin trading volume, the CSRC implemented the refinancing scheme in August 2012, allowing margin traders to borrow money from banks, insurance companies, mutual funds, among other lending source. To maintain the stability of the stock market, CSRC approves a limited number of financial agents to lend on securities. CSRC also made changes to the rules of margin trading and short selling to regulate the market after the stock crash occurred in July 2015. First, to reduce market manipulation, the declared price of short-selling stock should be higher than the latest transaction price of this security. Second, the time pattern of short selling has changed from "T+0" to "T+1"[17] to reduce the speculation. Third, the margin requirement of margin trading has increased from 50% to 100%. Last, the static price-to-earnings ratio is limited to the normal range between 0 and 300.

3.4. Data Sample Description and Methodology

We obtain both daily and monthly stock returns, along with quarterly accounting data and information on designated stocks from the Chinese Stock Market & Accounting Research (CSMAR) database. The information of designated stocks allowed for margin trading and short

[16] Huatai Securities Research Report shows the percentage of trading accounts for margin traders and short sellers. https://crm.htsc.com.cn/doc/2019/10740101/43a1ded8-75e5-48bf-8b5e-7ca2e2e29058.pdf
[17] Changing from "T+0" to "T+1" means that short sellers borrowing stocks must wait for one day to sell their stocks. Short sellers are forbidden to sell stocks on the same day in which they borrow them.

selling includes margin-trading volume, short-selling volume, its corresponding covering volumes and its corresponding balances. To construct the misvaluation measure, we collect forecasted earnings per share from the Refinitiv I/B/E/S database. We obtain the industry classification standard from the Bloomberg industry classification system, including communication, consumer discretionary, consumer staples, energy, financials, healthcare, industrials, materials, technology and utilities. Our data sample starts on January 2010 and ends on 31 December 2020. The longer history stock-level trading data allows us to empirically investigate the imbalanced trading effect of the pilot programme on stock valuation, and yield a more comprehensive and less biased picture.

3.4.1. Main Explanatory Variables

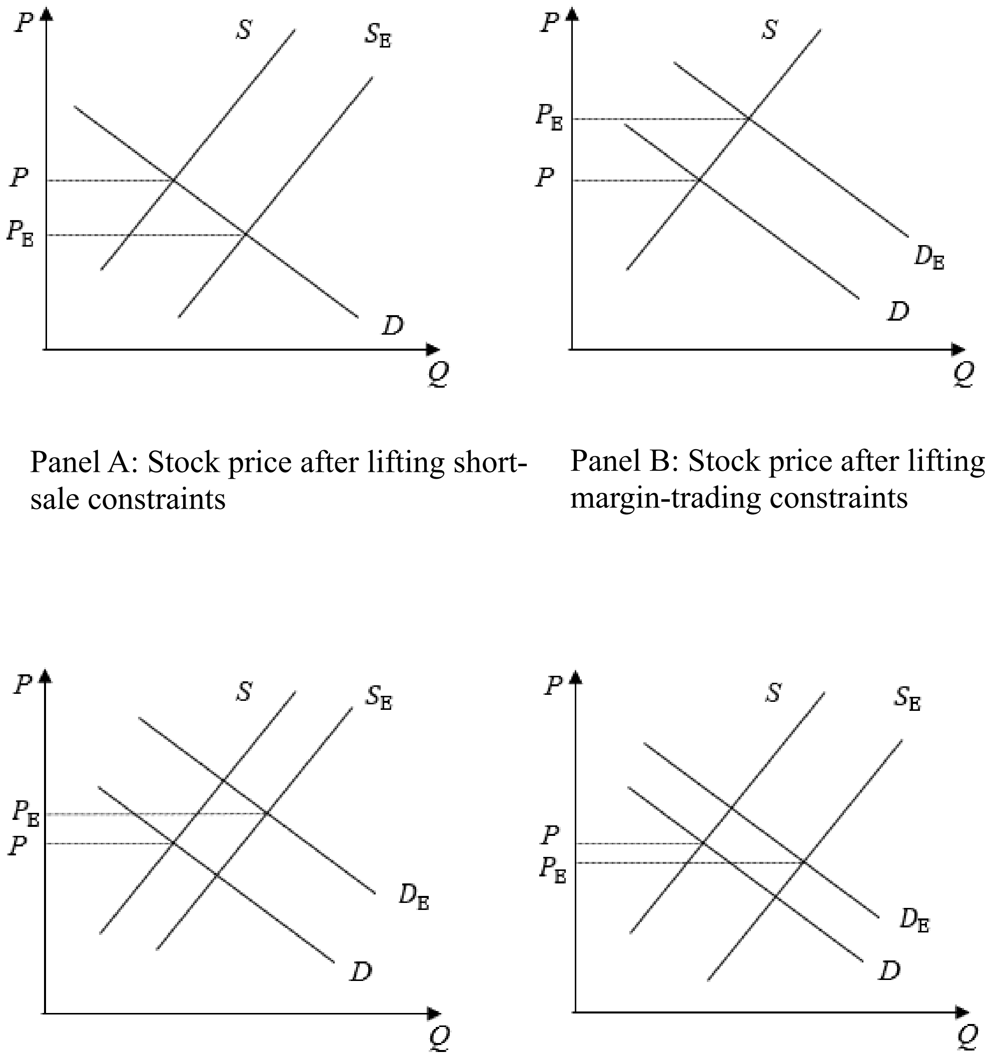
Previous study examines the sole role of either short sales or margin trades in influencing stock valuation (for example, Liu et al., 2020; Lv & Wu, 2020). However, the CSRC has lifted the ban not only on short sales, but also on margin trades. The short sale measure alone cannot capture the trading difference between margin traders and short sellers (Li et al., 2018). Few studies have paid attention to the combined effect of margin trading and short selling on stock valuation. In the presence of a large trading divergence between margin trades and short sales, there are no well-documented measures to reveal the trading imbalance of both. We construct a margin trading – short selling (MS) index, based on the short-selling ratio of Li et al. (2018), as the difference between the margin-trading (MT) and short-sales (SS) amount balance scaled by tradable market shares. The margin-trading balance is the net amount of borrowed money that margin traders hold in a firm after deducting the money repayment. Similarly, a short-sale balance is defined as the net value of borrowed stocks that short sellers hold in a firm after deducting stock has been returned. The equation of the MS index is:

$$MS_i = \frac{margin\ trading\ balance_i - short\ selling\ balance_i}{market\ value\ of\ tradable\ shares_i} \quad (3.1)$$

In contrast to a short-selling balance as the numerator to examine the associated return predictive power in Li et al. (2018), we use the difference between margin-trading and short-selling balances to measure the associated trading dispersion. The price influence of short sales and margin trading can be viewed from a supply- and demand perspective. The extant literature shows that short sellers create a stock supply of a firm. Short sales increase the supply of stock in the market by the amount of the outstanding short position, resulting in a shift of the supply curve to the right and a decrease in the price (Miller, 1977). Likewise, margin trading caters to the stock demand of optimistic investors by allowing them to purchase stocks on margin (Basak & Croitoru, 2006; Frazzini & Pedersen, 2014). Margin trading moves the demand curve to the right, leading to a price increase (Li et al., 2018). Hence, our MS index, measuring trading imbalance in the pilot programme, reflects excess demand for a stock in the same trading period. A positive MS index indicates an excessive demand for a stock. A negative MS index indicates an excessive supply of a stock. The MS index can serve as an indicator to suggest whether a stock price is under upward or downward pressure.

To facilitate understanding of these arguments, Figure 3.1 shows the price changes subject to movements of the supply and demand lines. Lines S and D denote the supply and demand lines with margin-trading and short-sale constraints. Lines S_E and D_E denote the supply and demand lines without constraints. Panel A depicts a price decrease caused by an increasing stock supply after relaxing the short-sale constraints. Panel B depicts a price increase caused by an increasing stock demand after relaxing the margin-trading constraints. Panel C shows the potential upwards price movement caused by an excess demand (MS > 0) when the trading volume of margin traders is much higher than that of short sellers. In contrast, Panel D shows the potential downwards price movement caused by an excess supply (MS < 0).

Figure 3.1. Supply and demand curves



Panel A: Stock price after lifting short-sale constraints

Panel B: Stock price after lifting margin-trading constraints

Panel C: Stock price with excess demand (MS > 0)

Panel D: Stock price with excess supply (MS < 0)

The MS index contains information content. Early literature has well documented that short sellers and margin traders are information utilisers (Miller,1977; Diamond & Verrecchia, 1987). In other words, margin traders make demand decisions when they hold positive information, expecting stock prices will rise. Short sellers make supply decisions based on negative information, anticipating stock prices will decrease. The trading volumes of short sellers and margin traders should derive from the results of their reactions to the information. Hence, the MS index, capturing well the willingness of investors to purchase on margin or sell short for a stock in the same period, proxies for the net positive or negative views of the market about the stock. A positive MS index indicates that a stock is carrying/bearing net positive market information from eligible traders in the Chinese pilot programme. A negative MS index indicates that a stock is largely influenced by the excessive negative market information of eligible traders. In sum, the MS index also serves as an indicator of whether the information about the stock is, on average, good or bad.

We scale the MS index of a stock by the market value of its tradable shares to measure the trading imbalance relative to the total investment in the stock. The denominator allows us to eliminate the influence on pilot trading of the tradable shares associated with the normal trading mechanism.

Compared with the short-selling ratio of Li et al. (2018)[18], which only measures a relative value, our index can effectively capture the trading scale. For example, suppose the trading volume of short selling (SS) and margin trading (MT) are 8 million and 10 million, respectively, and the short-selling ratio of Li et al. (2018) is 0.44 (8/18). Suppose again, the trading volumes of SS and MT reduce to 0.8 million and 1 million, respectively. The short-selling ratio remains the same: 0.44 (0.8/1.8). In contrast, our MS index can reflect the variation of trading scale. Given the market value of tradable shares is 100 million, the MS index is 0.02 (2/100) and 0.002 (0.2/100) corresponding to the above two cases, respectively. Measuring the trading scale is important for investigating the trading influence on stock misvaluation. A

[18] The short-selling ratio is defined as the ratio of short-selling balance to the sum of both the short-selling and margin-trading balances.

higher trading scale means a higher investment willingness of investors, and vice versa. Furthermore, the MS index can provide more variation for examining stock misvaluation.

To mitigate the concern of scale differences between margin trading and short selling, we subtract the overall mean of the MS index from the MS index of a stock at the current trading period. We use this demeaned MS index, denoted as $\mathrm{MS}^{\mathrm{DM}}$, in regression analyses.

We also examine the effects of margin-trading activities (MT) and short-selling activities (SS) on stock misvaluation. MT is defined as the ratio of the margin-trading balance over the market value of tradable shares.

$$MT_i = \frac{margin\ trading\ balance_i}{market\ value\ of\ tradable\ shares_i} \tag{3.2}$$

SS is computed as the ratio of the short-sale balance over the market value of tradable shares.

$$SS_i = \frac{short\ selling\ balance_i}{market\ value\ of\ tradable\ shares\ _i} \tag{3.3}$$

3.4.2. Dependent Variable – Misvaluation Measure

We use stock misvaluation as the dependent variable of the regression model in this chapter. We use two misvaluation measures. The first one is the same stock misvaluation as in Chapter Two, denoted as MSVF. The latter is based on the method of Rhodes–Kropf et al. (2005) and Chang et al. (2013), denoted as $\mathrm{MSVF}_{\mathrm{Chang}}$. Using two measures can alleviate the concern that the influence of the $\mathrm{MS}^{\mathrm{DM}}$ index on stock misvaluation is subject to the ownership structure. The construction of stock misvaluation and a comparison of these two measures have been given in Section 2.3.1 of Chapter Two.

3.4.3. Control Variables

In the regression analysis, we use the following firm-level variables as control variables; the leverage ratio, profitability, capital expenditure, book-to-market ratio, volatility, and analyst coverage. Bofinger et al. (2022) document that these control variables are relevant in the context of misvaluation and use them as control variables to investigate stock misvaluation. The leverage ratio is defined as the total liabilities over the total assets (Dong et al., 2006). Profitability is defined as the operating income over the total assets (Eisdorfer et al., 2019). The capital expenditure (Hertzel & Li, 2010) is the logarithm of the sum of fixed assets and other relevant expenditures on purchasing fixed assets.

We control the market-to-book ratio which reflects the growth of firm valuation (Rhodes-Kropf et al., 2005 & Doukas et al., 2010). Moreover, volatility is the standard deviation of a firm's daily stock returns. Hwang and Lee (2013) document that high volatility accelerates the speed of market value adjustment. In addition, Becchetti et al. (2013) show that the analysts' coverage affects stock valuation. We include analyst coverage in our analyses[19]. Analyst coverage is the logarithm of total number of analysts providing "Buy", "Hold", or "Sell" stock reports for a firm.

[19] CSMAR provides analyst coverage data for firms. We treat the analysts' coverage as the sum of analysts who give "Buy", "Sell" or "Hold" recommendation reports for corresponding firms. Any firms with no analysts' coverage are defined as 0 as the analysts' coverage.

3.4.4. Methodology

With panel data we apply the fixed-effect panel regression model to investigate the effect of imbalanced margin trading and short sales on stock misvaluation. The fixed effect panel regression[20] model helps us rule out the individual fixed effect and time-invariant exogenous factors, therefore improving the explanatory power of the model. This regression equation is as follows:

$$y_{i,t} = \beta_0 + \beta_1 Dep_{i,t-1} + \beta_2 MS^{DM}_{i,t-1} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{3.4}$$

where $y_{i,t}$ denotes misvaluation measures[21] for each firm. β_0 captures a vector of the intercepts. $Dep_{i,t-1}$ [22]is the lagged one-period dependent variable. β_1 captures the effect of past stock misvaluation on its current stock misvaluation. $MS^{DM}_{i,t-1}$ is the demeaned MS index. Therefore, β_2 captures the impact of lagged imbalanced trades on stock misvaluation. $X_{i,t}$ represents a variety of control variables, which are shown in Section 3.4.3. β_3 are the parameters for the corresponding control variables relevant to the context of stock valuation. $\epsilon_{i,t}$ is the error term in this regression. We take a one-month lag for the $\mathrm{MS}^{\mathrm{DM}}$ index. The reason is that current market trading information could not be incorporated into simultaneous firms' prices (Hou & Moskowitz, 2005).

[20] The p-values of the F-test for all fixed effects panel regressions in Essay Two are less than 0.001. The significant p-value indicates that the fixed effects panel regression model is more suitable than the OLS regression model in our data sample, as the fixed effect is significant. We do not report this figure in tables for concise.

[21] We use two misvaluation measures in Essay Two. The first one refers to the MSVF derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions. The second one refers to the $\mathrm{MSVF}_{\mathrm{Chang}}$, which is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013).

[22] We denote the lagged dependent variable as $Dep_{i,t-1}$ and only apply it to the right-hand side of the regression equation to distinguish it from the dependent variable $y_{i,t}$. This denotation remains the same in equations (4.1) – (4.4) of Essay Three.

3.5. Results

3.5.1. Event Study

As mentioned earlier, we carry out a two-stage analysis. In the first stage, we adopt the event study approach of Chang et al. (2014)[23], but we expand the sample period to December 2020 from December 2012. We observe an average abnormal return of 0.641 (t=9.54) bps on the event day, as reported in Panel A of Table 3.1. We also find that the CAR[-1, +1], the cumulated abnormal return during three trading days on the event date and its adjacent days, is 0.871 (t=7.35) bps on average, as shown in Panel B of Table 3.1. The average CAR remains significantly positive up to 20 trading days after the event. Figure 3.2 shows the cross-sectional average of (cumulative) abnormal returns around event trading days, spanning a window of [-5, 25] relative to the event. We observe positive abnormal returns on most trading days and an upward trend of CAR across the window. These findings are consistent with the development of the Chinese pilot programme, which is characterised by intensified margin-trading activities.

Table 3.1. Stock returns around event-trading days

Panel A

Ave Ret	T-Value	Event Tra. Day
-0.42***	[-6.81]	-5
-0.108*	[-1.71]	-4
-0.351***	[-6.32]	-3
-0.096*	[-1.7]	-2
-0.004	[-0.06]	-1
0.641* **	**[9.54]**	**0**
0.234***	[4.13]	1
0.10*	[1.82]	2
0.358***	[5.89]	3
-0.027	[-0.46]	4
0.391***	[6.71]	5

Panel B

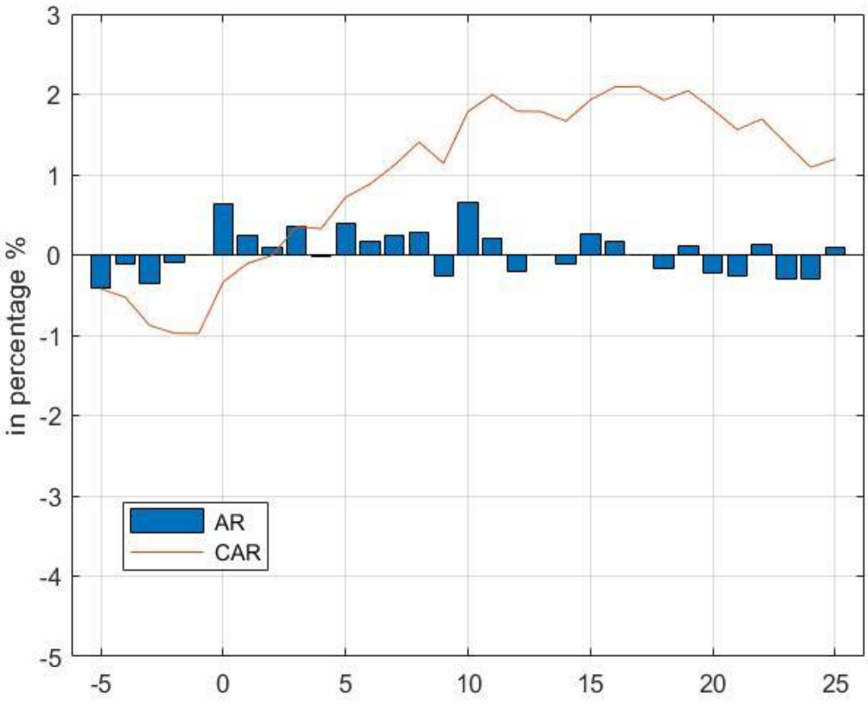
CAR	Ret	T-Value
[-5, -1]	-0.979***	[-6.86]

[23] Chang et al. (2014) find negative abnormal (cumulative) returns on (around) the event trading days. The average abnormal return is -0.47 (t=4.46) on the event trading day. The cumulated abnormal return CAR[-1, +1] is -0.53 (t=3.13).

[-1, +1]	0.871***	[7.35]
[0, +2]	0.974***	[8.76]
[0, +5]	1.697***	[10.62]
[0, +10]	2.765***	[12.6]
[0, +20]	2.792***	[9.08]
[0, +40]	0.481	[1.15]

Notes: This table is the application of the event study of Chang et al. (2014), extending the data sample period to the end of 2020. This table reports the cross-sectional mean of abnormal returns and cumulated abnormal returns as well as associated statistics around event trading days in Panel A and B, respectively. The abnormal return is calculated as the subtraction difference between the raw return and the market-model prediction return. In the market model, an estimation model of [-396, -31] in calendar days relative to the announcement day is applied, with a minimum length of 180 trading days. An event trading day is defined as a day when a stock is added to the designated list and therefore can be purchased on margin and sold short.

Figure 3.2. Abnormal (cumulative) returns around event-trading days



Notes: This figure is the application of the event study of Chang et al. (2014), extending the data sample period to the end of 2020. This figure plots the (cumulative) abnormal returns around event-trading days. An event-trading day is defined as a day when a stock is added to the designated list and therefore can be purchased on margin and sold short. The horizontal axis shows the event-trading days. The vertical axis shows the abnormal returns (Blue bar) and cumulative abnormal returns (Gold line). The abnormal return is the daily returns adjusted by the market model. In the market model, an estimation model of [-396, -31] in calendar days relative to the announcement day is applied, with a minimum length of 180 trading days.

We calculate the cross-sectional average of the MS index for each day within the event window of 20 days. We then compare the cross-section averages by applying the data period (P1) of Chang et al. (2014) and the whole data period (P2) in Table 3.2. We can see a positive average of the MS index in Panels A and B, implying that the trading volume of margin traders is higher than that of short sellers. We find that the cross-sectional average MS index (0.98%) of Panel B is around 10 times greater than that (0.09%) of Panel A throughout 20 trading days. In particular, the margin-trading balance is much higher than the short-selling balance. The higher MS index in P2 indicates an imbalanced development between margin-trading and short-selling activities due to the soaring margin trades. These findings are consistent with the results of Table 3.1. In our further analysis, to mitigate the concern of scale differences between margin trading and short selling, the overall time-series mean of the MS index over the entire sample is subtracted from the MS index of a stock at the current trading period, so called the demeaned MS index ($\mathrm{MS}^{\mathrm{DM}}$). The demeaned MS index on its mean can also remove the bias by effectively centring the data around zero.

Table 3.2. MS index around event-trading days

Panel A

Event Tra. Day	MS index	Margin trading	Short selling	M-S Dif.
0	0.02%	1854382	112323	1742059
1	0.02%	2517118	344670	2172448
2	0.03%	3404658	417501	2987157
3	0.04%	4720251	451560	4268693
4	0.05%	5399074	457124	4941951
5	0.06%	6298074	468071	5830004
6	0.07%	7369223	491026	6878195
7	0.07%	8185529	553612	7631916
8	0.09%	9717251	514864	9202388
9	0.09%	10260018	547579	9712440
10	0.10%	11334899	565631	10769267
11	0.11%	12218415	617745	11600662
12	0.11%	12357941	645249	11712700
13	0.12%	12944035	658267	12285770
14	0.12%	13383967	694724	12689242
15	0.13%	13947789	739234	13208559

16	0.14%	14761688	707224	14054462
17	0.15%	15528258	738399	14789859
18	0.15%	16058541	754378	15304169
19	0.16%	16815044	791148	16023904
20	0.17%	17497436	825660	16671776
Average	0.09%	10313028	575999	9737029

Panel B

Event Tra. Day	MS index	Margin trading	Short selling	MS Dif.
0	0.18%	15029326	16907	15012419
1	0.31%	25449730	76560	25373168
2	0.44%	35410012	100532	35309472
3	0.54%	44132816	123462	44009368
4	0.62%	50322440	127705	50194740
5	0.70%	56575480	137669	56437796
6	0.76%	61745012	154350	61590656
7	0.84%	68080056	198317	67881728
8	0.91%	73830048	221150	73608928
9	0.97%	78169392	274459	77894928
10	1.03%	84022744	302071	83720672
11	1.09%	89128336	348930	88779400
12	1.14%	93912352	406150	93506192
13	1.22%	100535336	497824	100037528
14	1.27%	104827688	546541	104281176
15	1.32%	111191232	612245	110579032
16	1.38%	116190344	645228	115545104
17	1.43%	119810272	659524	119150800
18	1.46%	122815960	670731	122145216
19	1.51%	127066096	699564	126366544
20	1.55%	129359552	612617	128746968
Average	0.98%	81314487	353930	80960564

Notes: This table shows the cross-sectional average of the MS index, the margin-trading balance, the short-selling balance and the margin-trading and short-selling difference (M-S Dif.) around event-trading days. Panel A shows the average of these target variables during the data sample period of Chang et al. (2014). Panel B shows the average of these target variables during the whole data sample period, extending to the end of 2020. The MS index is defined as the difference between the margin-trading and short-sales balances scaled by tradable market shares. The margin trading balance is the net amount of borrowed money that margin traders hold in a firm after deducting the money repayment. The short-sale balance is defined as the net value of borrowed stocks that short sellers hold in a firm after deducting stock repayments. The margin-trading and short-selling difference (M-S Dif.) is defined as the subtraction between the margin-trading and short-selling balance. To better observe the imbalanced situation of margin-trading and short-selling activities, the MS index of this table is not scaled by its overall mean.

3.5.2. Summary Statistics

Table 3.3 reports our main explanatory variables, the MS index, the $\mathrm{MS}^{\mathrm{DM}}$ index as well as the margin-trading ratio and short-selling ratio. The MS index is small across years and industries because the trading volumes of the Chinese pilot programme are comparatively much less than the normal trading volumes in the open stock market. $\mathrm{MS}^{\mathrm{DM}}$ index has the similar performance as the MS index. The margin-trading activities contribute much more to the MS index than short sales. The short sales ratio is only around 0.001% when it is scaled on the market value of tradable shares.

Table 3.3. The observations of MS index, $\mathrm{MS}^{\mathrm{DM}}$ index, margin-trading and short-selling ratios per year and by industry

Panel A

Year	Obs.	MS %	$\mathrm{MS}^{\mathrm{DM}}$ %	MT%	SS %
2010	590	0.044	0.031	0.044	0.000
2011	962	0.078	0.062	0.080	0.002
2012	2784	0.109	0.079	0.111	0.002
2013	5528	0.367	0.329	0.367	0.001
2014	7526	0.487	0.452	0.487	0.001
2015	8308	0.083	0.056	0.082	-0.001
2016	8529	-0.195	-0.221	-0.195	0.000
2017	9272	-0.049	-0.075	-0.049	0.000
2018	9470	-0.229	-0.256	-0.229	0.000
2019	12210	0.057	0.001	0.058	0.001
2020	15592	0.062	-0.020	0.069	0.007

Panel B

Industry	Obs.	MS %	$\mathrm{MS}^{\mathrm{DM}}$ %	MT%	SS %
Communications	2776	0.048	0.008	0.049	0.001
Consumer Discretionary	9130	0.052	0.013	0.053	0.001
Consumer Staples	5875	0.052	0.013	0.054	0.002
Energy	1934	0.046	0.012	0.047	0.002
Financials	5427	0.064	0.013	0.070	0.006
Real estate	5196	0.035	0.007	0.035	0.001
HealthCare	7430	0.050	0.008	0.051	0.002
Industrials	14864	0.044	0.005	0.045	0.001
Materials	15509	0.048	0.003	0.050	0.001
Technology	8998	0.080	0.016	0.082	0.002
Utilities	3632	0.039	-0.001	0.040	0.002

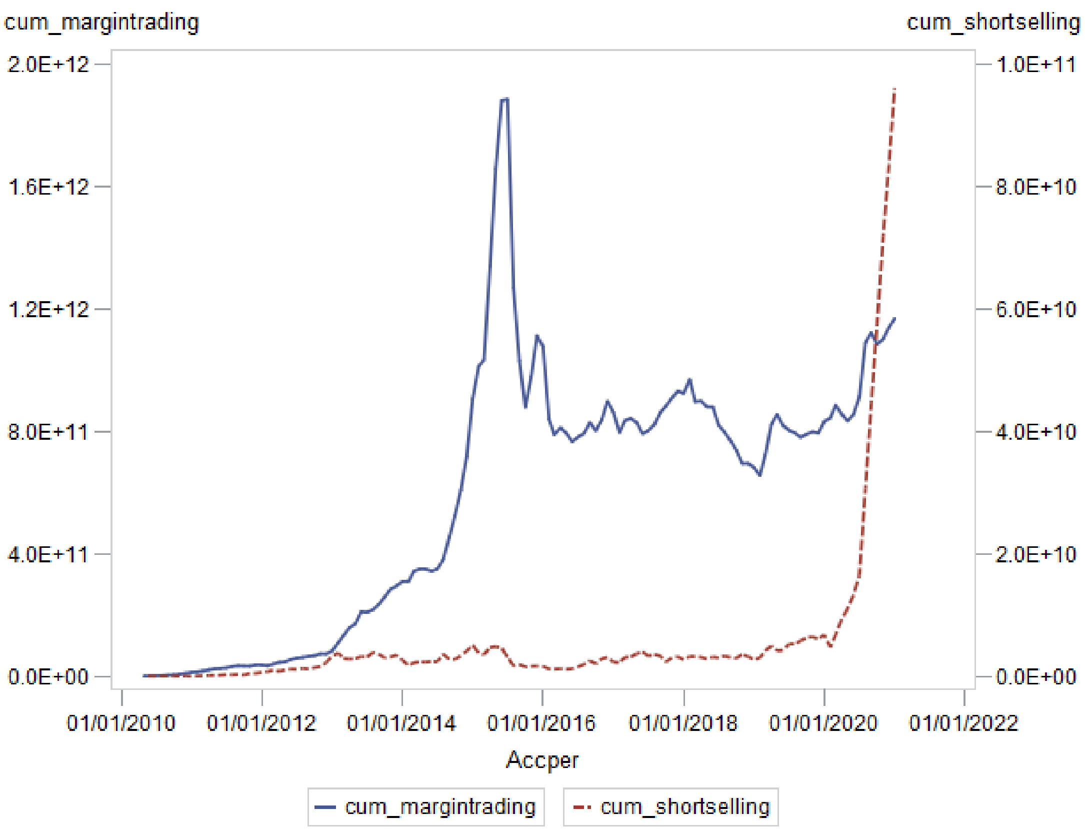
Notes: This table shows the cross-sectional mean value of MS index, $\mathrm{MS}^{\mathrm{DM}}$ index for each stock, margin-trading ratio (MT) and short-selling ratio (SS) in percentages for all firms in our data sample across years as well as industries. Industry classification is based on the Bloomberg sector codes. Obs. is the abbreviation of observation.

In Panel A, MS experiences an increase from 0.044% to 0.487% over the years 2010 to 2014, implying that the level of imbalance mainly derived from margin trading deteriorates during this period. The MS index decreases from 2015 until 2018, and then slightly reverses. We observe negative figures for the MS index between 2016 and 2018. The first underlying reason for this is that the Chinese stock market experienced a serious market crash[24] in July 2015. The market panic strikes investors' moods, especially margin traders who quickly react to the market downturn and repay the money that they had borrowed. The monthly average repayment of margin traders is more than the amount of borrowing from financial agents, thus leading to a negative margin-trading balance. We can see that negative MS is associated with negative MT. Second, CSRC updates the rules of the pilot programme and adds additional terms to regulate the Chinese stock market after July 2015. The regulation of the Chinese government reduces the enthusiasm for leverage trading, especially margin trading, with the MT ratio reducing to 0.069% in 2020. This figure approaches the one (0.044%) in 2010. In contrast, the short-sale ratio (SS) increases to 0.007% (2020), which is triple that of 2011, even if the short-sale balance still accounts for a comparatively small part of the market. These updated regulations may decrease the level of Chinese uninformed trading in the pilot programme. A comparison of the market aggregated margin-trading and short-sale balance is shown in Figure 3.3. We observe that the gap between the cumulative margin-trading balance and short-selling balance is comparatively small in the early period. After the end of 2012, the

[24] In mid-2015, the Chinese stock markets experienced a severe market crash. The Shanghai Stock Exchange Composite Index (SSE index) dropped from 5178 to 2850 after two rounds of slumps in 53 trading days. This market crash represents a decline of more than 45%.

imbalanced situation becomes increasingly severe until late 2015, followed by a sharp decline due to the stock crash. The gap between margin trading and short selling maintains a steady level until the end of 2019, followed by a sharp increase of short-selling activities in 2020.

Figure 3.3. Market aggregated margin-trading balance and short-selling balance



Notes: This figure shows the cumulative margin-trading balance and short-selling balance over March 2010 to December 2020. The solid blue and dotted red lines indicate the balance of margin trading and short selling, respectively.

In Panel B, we observe that MS varies across industries, suggesting that Chinese investors have different opinions about eligible firms in different industries. The highest MS (0.08%) is in the technology sector, because the technology industry has experienced rapid development in the last decade. Hence, the purchasing willingness of investors is much higher for high-tech firms than for firms in other sectors. It is not surprising to see a high MS in the technology sector, driven by a high margin-trading activities. The MT ratio of the technology sector is 0.082%. The real estate sector experienced a market downturn in the last decade.

Hence, we observe a comparatively low MS caused by the low margin-trading activities. We observe a lowest MT ratio in the real estate sector (0.035%).

Table 3.4 shows the descriptive statistics of the dependent variables and independent variables. The mean value of MSVF is 0.207, indicating that eligible firms in the pilot programme tend to be slightly overvalued. The mean and median values of MSVF are slightly lower than $\mathrm{MSVF}_{\mathrm{Chang}}$. The difference is derived from the ownership classification when estimating the true value of firms in the misvaluation benchmark regression. Moreover, the MS index shows a mean value of 0.064%, which is mainly contributed by margin trading. We can see that MT_{-1} shows a mean value of 0.065%, while short selling (SS_{-1}) only has a mean value of 0.002%. The total trading volume of the Chinese pilot programme is dominated by margin traders. The trading volume of margin traders and short sellers is severely imbalanced. Not surprisingly, the $\mathrm{MS}_{-1}^{\mathrm{DM}}$ index (0.020) is smaller than the MS_{-1} index. In addition, the mean value of the leverage ratio signals that almost half of the total assets are occupied by the total liabilities. The average value of the market-to-book ratio indicates that the market value is 8.037 times higher than the book value of a firm. Furthermore, on average, each firm in our data sample is covered by two analysts.

Table 3.4. Descriptive statistics of dependent and explanatory variables

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Panel A: Misvaluation measures						
MSVF	69483	0.207	0.153	0.485	-1.541	2.370
$\mathrm{MSVF}_{\mathrm{Chang}}$	69483	0.253	0.214	0.498	-1.011	1.941
Panel B: Variables						
MS_{-1} (%)	69484	0.064	0.006	1.011	-0.184	0.138
$\mathrm{MS}_{-1}^{\mathrm{DM}}$(%)	69484	0.020	-0.031	1.005	-0.178	0.136
MT_{-1} (%)	69484	0.065	0.007	1.011	-0.184	0.138
SS_{-1} (%)	69484	0.002	0.000	0.040	-0.028	0.043
Lev	69439	0.494	0.498	0.199	0.076	0.938
Profitability	69439	0.032	0.021	0.039	-0.080	0.202
Capex	69439	20.325	20.316	1.511	15.597	24.502
Market-to-Book	69439	8.035	6.267	5.955	1.469	43.236
Volatility	69439	0.020	0.018	0.010	0.006	0.062
Analyst Coverage	69439	2	1	3.966	0	53

Notes: This table shows the summary statistics of the dependent variables and explanatory variables, including total observations, the mean values, the median values, the standard deviations, the minimum values and the maximum values. MS_{-1} (%) is the original MS index computed from equation (3.1) of this chapter. $\mathrm{MS}_{-1}^{\mathrm{DM}}$(%) is the demeaned MS index. MT_{-1} (%) is the margin-trading ratio reported in percentages. SS_{-1} (%) is the short sales ratio reported in percentages. Lev, Profitability, Capex, Market-to-Book, Volatility, and Analyst Coverage are control variables in this chapter.

3.5.3. The Relation Between $\mathrm{MS}^{\mathrm{DM}}$ and Stock Misvaluation

This section is relevant to the second stage of this chapter. In this section, we investigate the direct effect of eligible companies' imbalanced trading activities on stock misvaluation. We find a positive effect of the $\mathrm{MS}^{\mathrm{DM}}$ on misvaluation, implying the imbalanced trading between margin trading and short selling leads to stock misvaluation. We also separately examine the effect of margin trading and short sale on misvaluation to determine which one contributes more to the misvaluation. We find both significantly affect misvaluation in different directions. Margin trading positively affects misvaluation, while short sale negatively affects misvaluation. The explanatory power of the $\mathrm{MS}^{\mathrm{DM}}$ index on misvaluation mainly derives from margin trading. The underlying reason is that the demand from margin traders significantly outpaces the supply from short sellers, resulting in a price surge and consequently leading to an overvaluation of the stock.

There are ten regression models in Table 3.5. Model 1 reveals a positive effect of the $\mathrm{MS}^{\mathrm{DM}}$ index on misvaluation, which is 0.747 (t=9.34). The coefficient is significantly different from zero at the 1% significance level. A one unit of standard deviation (0.01) increase on MS_{-1} leads to the increase in stock misvaluation of 0.78%. We also find (Dep_{-1})[25] positively and significantly affects misvaluation, implying that current stock misvaluation is affected by past stock misvaluation as misvaluation persists for a period. This finding is consistent when we incorporate control variables into the regression in model 2. The magnitude of MS_{-1}'s coefficient varies only slightly. Control variables do not subsume the explanatory power of

[25] The t-value of Dep_{-1} is larger than 100 in Table 3.5. The large T-value is caused by the small dispersion of the misvaluation measure. We construct monthly stock misvaluation by an impairment between the monthly market capitalisation of a firm and the annually estimated intrinsic value. This approach allows us to examine more detailed trading information from the pilot programme on stock misvaluation. While the misvaluation of a firm may not vary a lot in the same year. To rule out the concern that our finding is not subject to the data frequency, we re-run the models of Table 3.5 by using annualised data. We find the t-value of Dep_{-1} is around 10, upholding the previous finding. We report the annualised results in Appendix A.2.

MS_{-1} on stock misvaluation. Moreover, the profitability of a firm is negative and significantly associated with the misvaluation. Undervalued firms tend to be profitable (Eisdorfer et al., 2019). Hence, firms with high profits are associated with a low misvaluation measure. Market-to-book, volatility and analyst coverage are positively associated with misvaluation. Market-to-book measures whether a company is overvalued compared to its market capitalisation. A higher market-to-book ratio indicates a potential overvaluation, or a correction of undervaluation. In addition, firms with a higher number of analysts are more likely to be large and leading firms, which attract investors to price higher.

To see how important it is to control for past stock misvaluation (Dep_{-1}), we add column (3). The effect of MS_{-1} on misvaluation still remains positive and significant. The coefficient magnitude of MS_{-1} becomes about six times larger than its' coefficient values in models 1 and 2. The R square also decreases from 91.10% to 74.99%. This finding highlights the importance of incorporating Dep_{-1} into regressions, as stock misvaluation possesses autocorrelation behaviour.

To identify which, MT or SS, contributes to the positive effect of the $\mathrm{MS}^{\mathrm{DM}}$ index on misvaluation, we separately[26] investigate the margin trading and short selling in models 4 and 5. According to model 4, margin trading (MT_{-1}) also has a positive and significant effect on misvaluation. In particular, the coefficient magnitude of MT_{-1} is similar to MS_{-1}'s coefficient in model 2. The reason for this is that the trading volume of margin trading dominates the total trading volume of the Chinese pilot programme, where positive market information reflected in stock price is much higher than the negative information from short selling. The large information gap[27] will probably lead to stock overvaluation through the imbalanced trading in

[26] In Appendix A.3, we test the impact of margin trading and short selling on stock misvaluation, by simultaneously joining both into regressions. Our findings are robust.

[27] In Appendix A.4, we test the impact of $\mathrm{MS}_{-1}^{\mathrm{DM}}$ on stock misvaluation during the sample period of Chang et al. (2014). Our results reveal that $\mathrm{MS}_{-1}^{\mathrm{DM}}$ negatively related with stock misvaluation, suggesting that the margin-trading and short-selling activities contribute to reducing stock misvaluation in early periods. This finding aligns

the pilot programme. Meanwhile, from model 5, short sales (SS_{-1}) negatively affects misvaluation. The coefficient of short sale is much larger than that of MT, as the observed value of MT is much higher than that of SS. The negative sign of SSt_{-1} implies that allowing short selling benefits market efficiency. However, when margin trading is taken into account, the imbalanced trading volume will lead to misvaluation. This finding can be explained from the demand and supply perspective. After lifting the short-sales ban, short-selling activities push the supply curve to the right, leading to a price decrease and resulting in an undervaluation of stocks. When the demand line of margin trades is considered, the significant large-scale margin trades shift the demand curve to the right, resulting in a price increase and causing an overvaluation of stocks.

We test the relationship between the MS^{DM} index and stock misvaluation by using the misvaluation measure of Chang et al. (2013) across models 6 to 10. We can see the results remain qualitatively the same; the coefficient magnitude of MS_{-1} changes only by a small amount. Hence, our findings are not affected by ownership classification. Additionally, we have executed regression models 1-10 of Table 3.5 with the inclusion of a one-period lag for control variables. This approach is employed to address concerns regarding potential autocorrelation bias in our findings. The results pertaining to this matter are detailed in Appendix A.5.

Stock misvaluation can indicate the overvaluation and undervaluation through its sign, while not directly quantifying the extent of misvaluation. To explicitly capture the extent of misvaluation attributable to the MS^{DM} index as well as the margin-trading and short-selling activities, we introduce the absolute size of the MSVF as the dependent variable in Table 3.6. The absolute value of misvaluation allows us to better capture the divergence between the observed and intrinsic value. We find that results of Table 3.6 remain consistent with those of

with the fact that the extent of imbalance in margin trading and short selling is relatively modest during early periods.

Table 3.5. The positive signs on $\mathrm{MS}^{\mathrm{DM}}$ index and margin trading indicate that the imbalanced trading and margin trading increase stock misvaluation. The negative sign on short selling suggests that short-selling activities reduce stock misvaluation.

Table 3.5. Company misvaluation regressed on the MS^{DM} index

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	0.017***	0.038	0.267	0.038	0.038	-0.001	0.277***	1.61***	0.277***	0.273***
	[7.95]	[0.68]	[1.14]	[0.68]	[0.68]	[-0.81]	[4.53]	[5.36]	[4.53]	[4.46]
Dep_{-1}	0.82***	0.791***		0.791***	0.795***	0.884***	0.848***		0.848***	0.85***
	[185.06]	[158.05]		[158.08]	[163.5]	[305.14]	[245.15]		[245.19]	[248.71]
MS^{DM}_{-1}	0.747***	0.664***	4.015***			0.794***	0.708***	3.633***		
	[9.34]	[8.43]	[29.78]			[9.56]	[8.66]	[28.17]		
MT_{-1}				0.658***					0.699***	
				[8.37]					[8.56]	
SS_{-1}					-3.05**					-5.009***
					[-2.53]					[-3.59]
Lev		0.002	0.166**	0.002	0.001		0.039**	0.387***	0.039**	0.038**
		[0.13]	[2.32]	[0.13]	[0.08]		[2.14]	[4.09]	[2.14]	[2.08]
Profitability		-0.16***	0.292***	-0.16***	-0.157***		-0.246***	0.318***	-0.246***	-0.242***
		[-4.67]	[3.08]	[-4.67]	[-4.63]		[-6.76]	[2.78]	[-6.76]	[-6.68]
CapEx		-0.003	-0.005	-0.003	-0.003		-0.017***	-0.078***	-0.017***	-0.016***
		[-1.11]	[-0.39]	[-1.11]	[-1.15]		[-5.26]	[-5.04]	[-5.26]	[-5.22]
Market-to-Book		0.001***	0.002***	0.001***	0.001***		0.001***	0.003***	0.001***	0.001***
		[3.07]	[2.96]	[3.07]	[3.03]		[3.78]	[3.22]	[3.78]	[3.73]
Volatility		2.515***	5.057***	2.515***	2.539***		2.701***	7.395***	2.701***	2.728***
		[24.36]	[24.98]	[24.36]	[24.39]		[24.58]	[27.4]	[24.58]	[24.61]
Analyst Coverage		0.003***	0.013***	0.003***	0.003***		0.002***	0.013***	0.002***	0.002***
		[14.01]	[19.08]	[14.01]	[13.92]		[9.67]	[18.51]	[9.66]	[9.64]
Obs.	62871	62865	62866	62865	62865	62871	62865	62866	62865	62865
R-square	90.62%	91.10%	74.99%	91.10%	91.08%	91.64%	92.16%	68.16%	92.16%	92.15%

Notes: This table reports the fixed effect estimations of the effect of an eligible firm's lagged MS^{DM} index on its respective misvaluation. The dependent variables are misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Table 3.6. The absolute value of stock misvaluation regressed on the MS^{DM} index

Variables	(1) |MSVF|	(2) |MSVF|	(3) |MSVF|	(4) |MSVF|	(5) |MSVF|	(6) $\lvert MSVF_{Chang} \rvert$	(7) $\lvert MSVF_{Chang} \rvert$	(8) $\lvert MSVF_{Chang} \rvert$	(9) $\lvert MSVF_{Chang} \rvert$	(10) $\lvert MSVF_{Chang} \rvert$
Constant	0.06***	-0.767***	-1.626***	-0.767***	-0.784***	0.047***	-0.635***	-1.384***	-0.635***	-0.64***
	[27.34]	[-10.98]	[-9.47]	[-10.98]	[-11.19]	[18.52]	[-9]	[-26.01]	[-9]	[-9.07]
$\lvert Dep_{-1} \rvert$	0.753***	0.638***		0.638***	0.638***	0.793***	0.661***		0.661***	0.661***
	[158.63]	[96.69]		[96.69]	[97.29]	[166.73]	[93.42]		[93.42]	[93.5]
MS_{-1}^{DM}	1.357***	0.8***	0.932***			0.739***	0.184**	0.15*		
	[12.84]	[8.29]	[7.49]			[8.92]	[2.44]	[1.75]		
MT_{-1}				0.793***					0.18**	
				[8.24]					[2.39]	
SS_{-1}					-2.932**					-2.579*
					[-2.42]					[-1.79]
Lev		-0.11***	-0.19***	-0.11***	-0.112***		-0.097***	-0.171***	-0.097***	-0.097***
		[-5.5]	[-3.91]	[-5.5]	[-5.56]		[-5.01]	[-10.62]	[-5.01]	[-5.03]
Profitability		-0.498***	-0.779***	-0.498***	-0.493***		-0.643***	-1.126***	-0.643***	-0.642***
		[-10.98]	[-8.84]	[-10.98]	[-10.86]		[-13.04]	[-29.26]	[-13.04]	[-13.01]
CapEx		0.036***	0.079***	0.036***	0.037***		0.03***	0.069***	0.03***	0.03***
		[10.09]	[8.96]	[10.08]	[10.22]		[8.15]	[25.44]	[8.14]	[8.19]
Market-to-Book		0.02***	0.047***	0.02***	0.02***		0.02***	0.052***	0.02***	0.02***
		[30.46]	[38.69]	[30.46]	[30.59]		[29.98]	[143.78]	[29.98]	[30.23]
Volatility		0.742***	1.53***	0.741***	0.777***		0.675***	1.019***	0.675***	0.685***
		[6.78]	[8.57]	[6.77]	[7]		[6.42]	[9.7]	[6.42]	[6.5]
Analyst Coverage		0.002***	0.001***	0.002***	0.002***		0.001***	0.001***	0.001***	0.001***
		[6.79]	[2.91]	[6.79]	[6.73]		[3.45]	[4.67]	[3.45]	[3.45]
Obs.	48582	48576	48577	48576	48576	48582	48576	48577	48576	48576
R-square	78.53%	80.93%	62.92%	80.93%	80.87%	81.39%	83.75%	66.04%	83.75%	83.75%

Notes: This table reports the fixed effect estimations of the effect of an eligible firm's lagged MS^{DM} index on the absolute value of stock misvaluation. The dependent variables are the absolute value of misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering the ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

3.5.4. MS^{DM}-Misvaluation Relationship for Over- and Undervalued Firms

The previous section has shown that the imbalanced trade of the pilot programme affects stock-level misvaluation. However, the positive sign of the MS^{DM} index can only explain the overall misvaluation of a firm. A further question is whether MS could cause either overvaluation or undervaluation in different ways.

To examine whether a rise in the MS^{DM} index leads to a rise in overvaluation or a fall in undervaluation or both, we divide all firms of our data sample into most over- and undervalued groups based on the degree of misvaluation. The overvaluation group contains the top 30% of overvalued firms, while the undervaluation group contains the bottom 30% of undervalued firms. Table 3.7 shows the effect of the MS^{DM} index on misvaluation measures for the two groups. We find positive and significant effects of the lagged MS^{DM} index on the over- and undervalued groups for both misvaluation measures. A given change (rise or fall) of the MS^{DM} index impacts the overvalued and undervalued groups differently. Overvalued firms that experience increasing pressure of imbalanced trades become more overvalued. In contrast, undervalued firms facing increased imbalanced trades of the pilot programme become less undervalued. In a word, increasing imbalanced trades lessen undervaluation towards zero, while driving overvaluation further above zero.

Margin trading (MT_{-1}) also reveals a positive and significant coefficient in both the overvalued and undervalued groups in Table 3.7. The coefficient magnitude of MT_{-1} in model 4 is close to MS_{-1}^{DM} in model 2. This finding is consistent with Table 3.5, implying that margin trading mainly contributes to the positive effect on MS^{DM}. Importantly, the positive effect of MT_{-1} on undervaluation reveals that margin-trading activities could improve price efficiency by correcting the stock undervaluation. In contrast to Chang et al.'s (2014) study[28], which considers margin traders as non-information providers, we contend that margin traders serve as information conveyors, even though margin-trading activities may also contribute to overvaluation. Moreover, we find SS_{-1} shows a negative effect on overvaluation (Panel A), indicating that short selling decreases overvaluation. Combined with the result of Table 3.5, the short selling corrects misvaluation by decreasing existing overvaluation. In Panel B, SS_{-1} reveals a negative coefficient on $\mathrm{MSVF}_{\mathrm{Chang}}$ in the undervalued group, while the coefficient is insignificant on MSVF. From this inconsistent result, we are not able to conclude that SS_{-1} expands the undervaluation.

Our results can be explained from two[29] aspects. First, the trade dominated by margin traders could push up stock prices to some extent, thus impacting stock misvaluation, even if the eligible volume released by CSRC is comparatively much less than that of normal trading markets. Second, a higher degree of the imbalanced trading (MS index > 0) is perceived as a signal that a firm is more valuable and welcomed by qualified investors who are allowed to engage in margin trading and short selling, thereby attracting capital flows. As a result, this effect could impact the market valuation of firms regardless of the existing level of misvaluation.

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[28] In Appendix A.6, we regress overvaluation and undervaluation on $\mathrm{MS}_{-1}^{\mathrm{DM}}$ index using the sample period of Chang et al. (2014). The coefficient on $\mathrm{MS}_{-1}^{\mathrm{DM}}$ index shows a negative and significant sign on overvaluation, suggesting that margin-trading and short-selling activities in early periods reduce overvaluation, therefore improving price efficiency. This finding aligns with the notion of Chang et al. (2014) that short selling enhances price efficiency by incorporating negative information into prices.

[29] These two reasons just explain our results from the perspective of the Chinese pilot programme. However, there may be a contagious effect from pilot stock to normal stocks in terms of valuation. Investors may perceive pilot stocks as “high-quality” stocks with better performance than non-pilot stocks and tend to have more willingness to purchase pilot stocks, leading to stock misvaluation.

Table 3.7. The effect of the MS^{DM} index on the most overvalued (top 30%) and undervalued (bottom 30%) firms

Panel A Stock Overvaluation

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	0.231***	0.21**	0.324	0.21**	0.214***	0.222***	0.271***	0.46*	0.271***	0.289***
	[26.6]	[2.31]	[1.41]	[2.31]	[3.16]	[30.92]	[2.78]	[1.86]	[2.78]	[3.63]
Dep_{-1}	0.652***	0.632***		0.632***	0.634***	0.703***	0.658***		0.658***	0.752***
	[44.09]	[42]		[42]	[87.24]	[59.12]	[50.9]		[50.89]	[80.92]
MS^{DM}_{-1}	0.641***	0.424***	2.339***			1.014***	0.972***	2.413***		
	[4.21]	[2.79]	[11.95]			[7.8]	[7.88]	[15.85]		
MT_{-1}				0.417***					0.968***	
				[2.74]					[7.86]	
SS_{-1}					-2.943*					-4.104*
					[-1.67]					[-1.91]
Lev		0.052*	0.241***	0.052*	0.051**		0.13***	0.443***	0.13***	0.094***
		[1.69]	[3.19]	[1.69]	[2.53]		[3.84]	[4.54]	[3.84]	[3.25]
Profitability		-0.228***	0.034	-0.228***	-0.227***		-0.288***	0.109	-0.288***	-0.311***
		[-5.39]	[0.51]	[-5.39]	[-4.1]		[-5.36]	[1.1]	[-5.36]	[-5.33]
CapEx		-0.002	0.005	-0.002	-0.002		-0.006	-0.006	-0.006	-0.011***
		[-0.44]	[0.44]	[-0.44]	[-0.83]		[-1.29]	[-0.49]	[-1.29]	[-2.59]
Market-to-Book		0.001***	0.001**	0.001***	0.001***		0.001***	0.003***	0.001***	0.001***
		[2.62]	[2.54]	[2.62]	[4.4]		[3.47]	[3.44]	[3.47]	[3.38]
Volatility		2.175***	2.86***	2.175***	2.205***		2.297***	4.048***	2.297***	2.698***
		[13.74]	[12.78]	[13.74]	[14.17]		[15.54]	[16.77]	[15.54]	[14.83]
Analyst Coverage		0.002***	0.006***	0.002***	0.002***		0.002***	0.006***	0.002***	0.001***
		[9.47]	[12.76]	[9.46]	[10.7]		[8.5]	[11.75]	[8.49]	[5.78]
Obs.	22701	22695	22697	22695	22695	22792	22786	22788	22792	22695
R-square	77.86%	79.18%	56.96%	79.18%	79.16%	77.37%	79.22%	53.02%	77.37%	86.08%

Panel B Stock Undervaluation

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	-0.204***	-0.338***	-0.599***	-0.339***	-0.338***	-0.118***	-0.06	0.05	-0.084	-0.062
	[-45.55]	[-3.19]	[-3.14]	[-3.2]	[-3.22]	[-45.17]	[-0.41]	[0.06]	[-0.3]	[-0.17]
Dep_{-1}	0.566***	0.521***		0.521***	0.526***	0.647***	0.609***		0.654***	0.61***
	[48.76]	[44.96]		[44.95]	[45.9]	[55.97]	[29.06]		[14.06]	[11.35]
MS_{-1}^{DM}	0.59***	0.588***	1.664***			0.329***	0.192*	1.224**		
	[6.46]	[6.46]	[13.81]			[3.25]	[1.66]	[2.12]		
MT_{-1}				0.585***					0.41**	
				[6.43]					[2.08]	
SS_{-1}					-1.341					-4.973***
					[-0.83]					[-2.93]
Lev		-0.063**	-0.097*	-0.063**	-0.065**		-0.021	-0.042	-0.038	-0.021
		[-2.31]	[-1.79]	[-2.31]	[-2.4]		[-0.67]	[-0.33]	[-0.67]	[-0.35]
Profitability		0.026***	0.065	0.026***	0.026***		0.023***	0.078	-0.045	0.023
		[3.56]	[1.3]	[3.56]	[3.51]		[2.76]	[1.22]	[-0.67]	[1.03]
CapEx		0	-0.002	0	0.001		-0.01*	-0.029	-0.007	-0.01
		[0.08]	[-0.22]	[0.08]	[0.11]		[-1.86]	[-1.06]	[-0.83]	[-0.91]
Market-to-Book		0.016***	0.032***	0.016***	0.016***		0.011	0.027	0.008	0.011
		[9.84]	[10.04]	[9.84]	[9.89]		[1.39]	[0.56]	[0.43]	[0.48]
Volatility		0.767***	0.973***	0.767***	0.733***		2.262***	3.122***	2.365***	2.269***
		[7.55]	[6.52]	[7.54]	[7.08]		[17.13]	[4.97]	[10.85]	[9.63]
Analyst Coverage		0.002***	0.006***	0.002***	0.002***		0	0.006***	0	0
		[5.52]	[8.1]	[5.52]	[5.35]		[1.08]	[3.53]	[0.62]	[0.96]
Obs.	22944	22938	22939	22938	22938	22833	22827	22828	19348	22827
R-square	66.16%	67.97%	47.28%	67.97%	67.87%	73.86%	75.67%	47.74%	74.22%	75.76%

Notes: This table reports the fixed effect estimations of the effects of an eligible firm's lagged MS^{DM} index on its respective misvaluation for over- and undervalued firms. The dependent variables are misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), taking into consideration the ownership classification in benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

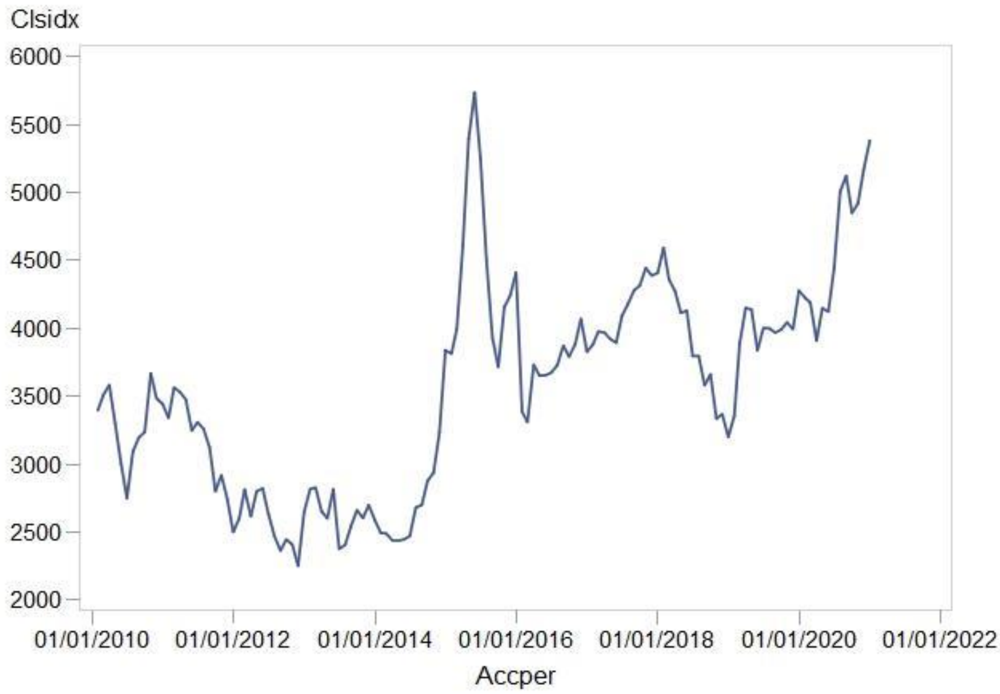
3.5.5. MS^{DM}-Misvaluation Relationship for Bull and Bear Markets

Investors' behaviour is different when they experience different market conditions. It is important to deal with this phenomenon by examining the underlying trading mechanism of the pilot programme to determine how sensitive margin traders and short sellers are to information about changing market conditions. These qualified investors may quickly switch from margin trading to short selling when the market goes down, thus leading to a decrease of the MS^{DM} index. Figure 3.4 shows the stock market trend from January 2010 to December 2020. We choose the CSI 800 index[30] to represent the Shanghai and Shenzhen stock markets. As the figure indicates, the index shoots up in 2015, followed by a sharply decrease. Consistently, the panel mean value of the MS^{DM} index has a similar performance to the CSI 800 index in 2015. The panel average MS^{DM} index is presented in Figure 3.5. One can see that the MS^{DM} index that carries investors' beliefs reacts sharply to the change in market conditions. We observe a negative MS^{DM} index in Figure 3.5. The negative figure is caused by a massive repayment when margin traders suffered the 2015 stock market crash. This occurrence probably leads to a decrease of the stock demand and a leftward shift of the demand curve. Given the demand curve remains unchanged, it is equivalent to the rightward shift of the supply curve.

Motivated by the two figures (Figure 3.4 and Figure 3.5), we further investigate the effect of imbalanced trades on stock misvaluation conditional on extreme market conditions. Following Chen et al. (2020), we use the CSI 800 index to gauge the whole market changes. A bull/bear market is identified when the market index continues to go up or down for at least three months and the magnitude of changes is more than 20%.

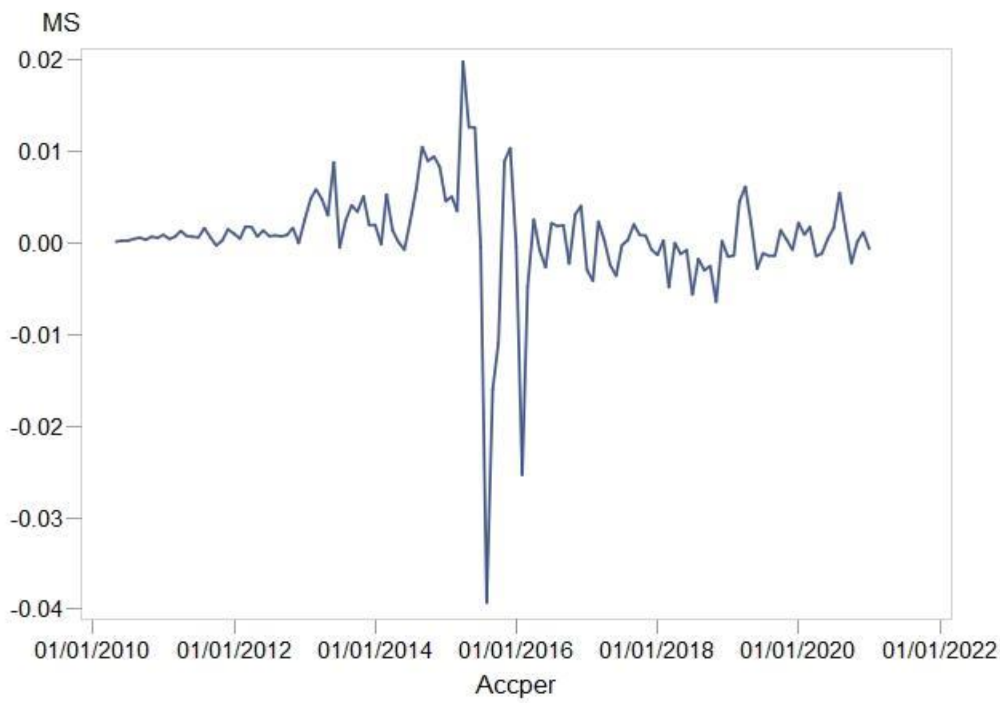
[30] The CSI 800 index contains listed firms of the CSI 300 index and the CSI small-cap 500 index. This index is made of stocks listed on the Shanghai and Shenzhen stock markets, comprehensively reflecting firms' performance with small, middle and large market capitalisation.

Figure 3.4. The CSI 800 index



Notes: This figure covers the period from Jan 2010 to Dec 2020. The bull market is identified when the market index return rises more than 20% over at least three continuous months, while a bear market is identified when the market index return decreases more than 20% over at least three continuous months (Chen et al., 2020).

Figure 3.5. The $\mathbf{MS^{DM}}$ index



Notes: This figure shows the panel mean value of MS^{DM} index for eligible stocks, which are allowed to be purchased on margin and sold short from March 2010 to December 2020.

Table 3.8 shows the effect of the lagged $\mathrm{MS^{DM}}$ index on the misvaluation measures for up- and downturn markets. From Panel A, $\mathrm{MS_{-1}}$ and $\mathrm{MT_{-1}}$ have positive significant effects on MSVF across models 1 to 4 during bull markets. The results remain for $\mathrm{MSVF_{Chang}}$ in models 6 to 9. This observation can be explained by the fact that investors have positive beliefs and tend to purchase stocks when the market has an upward trend, leading to a higher $\mathrm{MS^{DM}}$ index and, hence higher misvaluation. This is typical of positive feedback momentum. Hence, the positive effects of the $\mathrm{MS^{DM}}$ index on both misvaluation measures (MSVF and $\mathrm{MSVF_{Chang}}$) hold in the bull market periods. Models 5 and 10 reveal negative signs of $\mathrm{SS_{-1}}$'s coefficient for MSVF and $\mathrm{MSVF_{Chang}}$, respectively. Short sellers reduce the misvaluation during a bull market, even if the trading volume of short sellers is relatively small. Short sellers play a stabilising role in the stock market.

We now turn to Panel B, which shows the result for a bear market. $\mathrm{SS_{-1}}$ reveals a positive sign on the two misvaluation measures. This result is not surprising, as short-selling behaviours will exacerbate the downturn of the market and expand misvaluation. Short sellers may not promptly react to the market downturn to buy securities back in order to close a position.

Across both bull and bear markets, we observe that the coefficient of the $\mathrm{MS^{DM}}$ index in Panel A is greater than that of the $\mathrm{MS^{DM}}$ index in Panel B. This suggests a more pronounced relationship between the $\mathrm{MS^{DM}}$ index and misvaluation. During a bull market, investors tend to be optimistic and assume higher levels of risk-taking. Consequently, this imbalance between margin traders and short sellers increases, resulting in a more pronounced impact of the $\mathrm{MS^{DM}}$ index on misvaluation.

Table 3.8. Relationship between the MS^{DM} index and stock misvaluation in bull and bear markets

Panel A: Bull market

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	0.087***	-0.025	0.582*	-0.024	0.061	0.046***	0.594***	2.286***	0.596***	0.642***
	[17.28]	[-0.29]	[1.75]	[-0.27]	[0.64]	[14.09]	[7.02]	[5.77]	[7.04]	[6.75]
Dep_{-1}	0.777***	0.733***		0.733***	0.73***	0.875***	0.833***		0.833***	0.852***
	[102.5]	[83.24]		[83.4]	[79.24]	[174.93]	[105.07]		[105.29]	[102.4]
MS^{DM}_{-1}	0.58***	0.438***	0.446***			0.6***	0.491***	0.849***		
	[33.51]	[25.7]	[13.28]			[32.56]	[27.85]	[19.87]		
MT_{-1}				0.442***					0.496***	
				[25.8]					[28.02]	
SS_{-1}					-2.257***					-3.026***
					[-4.58]					[-5.86]
Lev		0.022	0.277***	0.022	0.011		0.051*	0.581***	0.051*	0.025
		[0.67]	[2.65]	[0.67]	[0.33]		[1.73]	[4.51]	[1.74]	[0.82]
Profitability		-0.348***	-0.007	-0.349***	-0.315***		-0.746***	-0.026	-0.747***	-0.726***
		[-5.11]	[-0.05]	[-5.13]	[-4.47]		[-8.22]	[-0.15]	[-8.23]	[-7.62]
CapEx		0.003	-0.015	0.002	-0.003		-0.03***	-0.109***	-0.03***	-0.033***
		[0.58]	[-0.85]	[0.54]	[-0.53]		[-6.95]	[-5.31]	[-6.99]	[-6.93]
Market-to-Book		0.001**	0.002	0.001**	0.001*		0.001*	0.003	0.001*	0.001*
		[1.99]	[1.36]	[1.99]	[1.83]		[1.95]	[1.41]	[1.95]	[1.88]
Volatility		4.402***	7.829***	4.38***	5.573***		3.844***	9.524***	3.819***	4.995***
		[21.12]	[19.56]	[21.05]	[23.93]		[20.03]	[18.21]	[19.95]	[22.53]
Analyst Coverage		0.003***	0.013***	0.003***	0.003***		0.001*	0.015***	0.001*	0.001*
		[7.7]	[13.32]	[7.67]	[8.14]		[1.79]	[14.32]	[1.76]	[1.67]
Obs.	13416	13402	13403	13402	13402	13416	13402	13669	13402	13402
R-square	90.27%	91.20%	77.82%	91.21%	90.59%	92.03%	92.81%	70.36%	92.82%	92.20%

Panel B: Bear market

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	0.154***	-0.405**	0.084	-0.408**	-0.604***	0.255***	-0.19	1.099***	-0.199	-0.162
	[17.98]	[-2.09]	[0.3]	[-2.11]	[-2.92]	[19.09]	[-0.9]	[2.72]	[-0.94]	[-0.79]
Dep_{-1}	0.429***	0.371***		0.371***	0.43***	0.63***	0.564***		0.565***	0.507***
	[26.97]	[20.35]		[20.35]	[25.89]	[42.5]	[32.65]		[32.65]	[30.35]
MS_{-1}^{DM}	0.151***	0.157***	0.313***			0.38***	0.406***	0.259***		
	[10.58]	[10.91]	[22.91]			[18.71]	[19.96]	[12.1]		
MT_{-1}				0.157***					0.406***	
				[10.91]					[19.94]	
SS_{-1}					14.158***					16.982***
					[3.47]					[4.14]
Lev		0.022	0.117	0.022	-0.006		0.203**	0.522***	0.203**	0.28***
		[0.23]	[0.83]	[0.23]	[-0.06]		[2.55]	[3.19]	[2.55]	[2.99]
Profitability		0.41***	0.689***	0.41***	0.442***		0.628***	1.316***	0.628***	0.791***
		[3.23]	[3.94]	[3.23]	[3.33]		[5.35]	[6.24]	[5.35]	[5.78]
CapEx		0.025**	0.002	0.025**	0.034***		0.017	-0.037*	0.017	0.015
		[2.31]	[0.14]	[2.31]	[2.96]		[1.49]	[-1.69]	[1.49]	[1.39]
Market-to-Book		0.001	0.001	0.001	0.001		0.001	0.002	0.001	0.001
		[1.05]	[1.07]	[1.05]	[1.05]		[0.97]	[1.07]	[0.97]	[1.13]
Volatility		2.225***	4.131***	2.225***	2.102***		3.095***	6.015***	3.095***	2.36***
		[8.01]	[9.63]	[8.01]	[7.79]		[10.55]	[10.54]	[10.55]	[8.2]
Analyst Coverage		-0.001	0.004**	-0.001	-0.004***		-0.004***	0	-0.004***	-0.004***
		[-0.82]	[2.44]	[-0.81]	[-2.97]		[-2.76]	[0.17]	[-2.77]	[-2.75]
Firm-year obs.	4158	4146	4147	4146	4146	4158	4146	4149	4146	4146
R-square	86.05%	86.69%	84.01%	86.69%	86.28%	88.45%	89.49%	81.70%	89.49%	87.37%

Notes: This table reports the fixed effect estimations of the effects of an eligible firm's lagged MS^{DM} index on its respective misvaluation during periods of bull market. A bull market is identified as being when the CSI 800 index return rises more than 20% for at least three continuous months. A bear market is identified as being when the CSI 800 index return decreases more than 20% for at least three continuous months (Chen et al., 2020). The dependent variables are the misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

3.5.6. Change of MS^{DM}-Misvaluation Relationship in Recent Periods

In the previous analysis, our results have shown that imbalanced trades between margin traders and short sellers lead to stock misvaluation. This effect holds for bull and bear markets. Moreover, we observe a highly sensitive reaction of the MS^{DM} index to stock market trends, implying eligible investors who are allowed to buy on leverage and sell short may change their trading strategies across different market conditions. This phenomenon is observed in 2015 when the Chinese stock market experienced a crash. The CSRC blames the slump of the stock market index on short sellers[31]. In fact, investors may switch the roles of margin traders and short sellers when the market environment changes. According to the basic statistics of pilot trading, a negative MS^{DM} index is mainly caused by the repayment of margin traders associated with the market downturn, rather than an increasing trading volume of short selling exceeding the margin trading. Hence, the power of short sellers who hold eligible stocks to decrease market returns is weak. Short sellers may directly sell short stock index options in the option market, instead of in the stock market. However, this concern is beyond our research scope.

In response to the stock market crash, Chinese stock market regulators implement a series of strict measures[32] to regulate pilot trading in the second half of 2015. As a result, the trading enthusiasm of the pilot programme decreases, and the malicious short-selling activities are cracked down on. One concern is that stricter regulation from the government will prevent short sellers from trading, thus preventing investors from incorporating market information

[31] The literature documents that short-selling activities are more prominent in mid-2015 (for example, Ni & Yin, 2020). However, they cautiously argue that other confounding events may also drive this result during the stock market crash in 2015.

[32] The Shanghai and Shenzhen stock markets were revised four times for the implementing regulations of margin trading and short selling since the 1st July 2015 (up to the beginning of 2016) when the Chinese stock market experiences serious stock disasters. Each update is shown as follows: 1. The declared ask price of stocks and funds which are eligible for selling short cannot be lower than the latest deal price; 2. Short sellers who borrowed stock for shorting at T0 need to wait at least one day (T1) to repay these borrowed stocks; 3. The margin requirement rate of margin traders increases from 50% to no less than 100%; and 4. The conversion ratio of stocks equals 0% if the static price-earnings ratio (P/E ratio) is more than 300 times or is negative.

into prices. In contrast, it also provides opportunities for margin traders to cool their enthusiasm and rule out noisy traders.

In order to test whether the periods after the implementation of new rules have temporal effects on stock misvaluation, we conduct an analysis through constructing a dummy variable for the more recent years, denoted as period. The dummy variable is defined as 1 when the period is from July 2015 to the end of our data sample. Otherwise, it equals 0 for the earlier period (March 2010 – June 2015). Additionally, we also construct an interaction variable between the lagged $\mathrm{MS}^{\mathrm{DM}}$ index (MT and SS) and the dummy variable to examine the effect of the $\mathrm{MS}^{\mathrm{DM}}$ index (MT and SS) on misvaluation in recent years.

Table 3.9 shows the results of the temporal effect on stock misvaluation. We find that the positive effect of the lagged $\mathrm{MS}^{\mathrm{DM}}$ index on both stock misvaluation measures (MSVF & $\mathrm{MSVF}_{\mathrm{Chang}}$) still holds. The positive effect is not subsumed by the past misvaluation (Dep_{-1}). Importantly, this table shows a negative effect of the recent period variable (Period) and the corresponding interactive term (MS_{Period}) on stock misvaluation, indicating that the positive $\mathrm{MS}^{\mathrm{DM}}$ index effect on stock misvaluation seems to be weaker in recent years. The recent period can influence the relationship between the $\mathrm{MS}^{\mathrm{DM}}$ index and misvaluation. Similarly, we observe the negative sign of $\mathrm{MT}_{\mathrm{period}}$ and positive sign of $\mathrm{SS}_{\mathrm{period}}$ in models 3 and 4, respectively. The result remains unchanged in models 7 and 8, suggesting that the margin-trading and short-selling activities in recent years have had their effects on misvaluation mitigated.

Table 3.9. Updated rules of CSRC after July 2015 stock disaster

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) $MSVF_{Chang}$	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$
Intercept	-0.395***	0.174	-0.396***	0.066	0.206***	1.296***	0.206***	0.199***
	[-6.02]	[0.78]	[-6.02]	[1.27]	[4.77]	[5.11]	[4.77]	[4.67]
Dep_{-1}	0.692***		0.692***	0.793***	0.845***		0.845***	0.847***
	[124.04]		[124.04]	[170.19]	[257.75]		[257.81]	[260.05]
Period	-0.009***	-0.106***	-0.009***	-0.018***	-0.019***	-0.036***	-0.019***	-0.022***
	[-2.86]	[-9.23]	[-2.89]	[-6.92]	[-8.8]	[-2.92]	[-8.87]	[-10.88]
MS_{Period}	-0.575***	-0.826***			-0.369**	-4.672***		
	[-4]	[-3]			[-2.45]	[-13.21]		
MT_{period}			-0.56***				-0.341**	
			[-3.9]				[-2.27]	
SS_{period}				0.577***				0.458***
				[7.65]				[5.64]
MS_{-1}^{DM}	0.804***	3.839***			0.816***	6.317***		
	[7.96]	[14.8]			[6.28]	[19.18]		
MT_{-1}			0.79***				0.787***	
			[7.84]				[6.08]	
SS_{-1}				-3.321***				-5.708***
				[-2.76]				[-3.99]
Lev	-0.147***	0.078	-0.147***	0.004	0.039***	0.283***	0.039***	0.037**
	[-7.43]	[1.11]	[-7.43]	[0.24]	[2.62]	[3.39]	[2.62]	[2.51]
Profitability	-0.528***	-0.034	-0.528***	-0.043***	-0.05**	-0.011	-0.05**	-0.05**
	[-14.7]	[-0.9]	[-14.7]	[-3.59]	[-2.17]	[-0.3]	[-2.17]	[-2.16]
CapEx	0.022***	0.013	0.022***	0	-0.01***	-0.057***	-0.01***	-0.009***
	[6.63]	[1.16]	[6.63]	[-0.14]	[-4.25]	[-4.3]	[-4.25]	[-4.07]
Market-to-Book	0.013***	0.002***	0.013***	0.001***	0.001***	0.004***	0.001***	0.001***
	[27.3]	[3.03]	[27.3]	[3.2]	[4.04]	[3.35]	[4.04]	[4.03]

Volatility	2.572***	4.905***	2.572***	2.507***	2.712***	7.363***	2.712***	2.736***
	[33.67]	[27.86]	[33.66]	[27.99]	[28.6]	[31.58]	[28.6]	[28.73]
Analyst Coverage	0.003***	0.013***	0.003***	0.003***	0.002***	0.013***	0.002***	0.002***
	[16]	[20.7]	[16]	[15.57]	[10.6]	[20.61]	[10.59]	[10.48]
Obs.	77919	77921	77919	77919	77919	77921	77919	77919
R-square	91.65%	74.40%	91.65%	91.04%	92.04%	67.87%	92.04%	92.03%

Notes: This table reports the estimations of the fixed effects of an eligible firm's lagged MS^{DM} index and recent period on its respective misvaluation. The recent period is a dummy variable, equalling 1 during the time span from July 2015 to Dec 2020, and 0 otherwise. The dependent variables are the misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

3.6. Robustness Check

Section 3.5.3 has shown that the lagged $\mathrm{MS^{DM}}$ index can positively and significantly affect the stock misvaluation measures. However, this relationship may be challenged by endogeneity concerns. One of the concerns is the reverse causality or simultaneity. In previous sections, we have already included a lagged $\mathrm{MS^{DM}}$ index (MT/SS) to alleviate this concern. We also included a lagged misvaluation to rule out the effect from past performance of stock misvaluation. The second concern is in regard to the estimation bias of omitted variables which affect misvaluation, even though we have carefully added control variables related to stock misvaluation from the literature and have used a fixed effect model to address this concern.

To alleviate endogeneity concerns, we adopt the dynamic GMM (generalised method of moments) regressions and two-stage least squares regressions methods. These results are reported in Table 3.10. In Panel A, we apply the dynamic GMM model, which has been used in asset pricing to mitigate the endogeneity issues (Mellado-Cid et al., 2018; Bofinger et al., 2022). This method adopts all independent variables with past lags as instrument variables. We continue to find a positive effect of the lagged $\mathrm{MS^{DM}}$ index ($\mathrm{MT_{-1}}$) and a negative effect of $\mathrm{SS_{-1}}$ on the two stock misvaluation measures. Additionally, we use AR (2) to test the serial correlation of the residuals. The p-value of AR (2) allows us to reject the null hypothesis of the serial correlation.

In Panel B, we apply the two-stage least squares regression. We treat the industry mean of the $\mathrm{MS^{DM}}$ index at each period as the instrument for the unbalanced trades of the pilot programme. The industry mean has been widely considered to be an instrument variable in the field of stock misvaluation. Bofinger et al. (2022) use the industry mean of sustainable investment to explore stock misvaluation. Drake et al. (2017) argue that peer stocks have similar trading patterns to comove with the market. The trading decision of investors should consider the aggregate information of the industry in which the target firm operates. We expect the industry means to be correlated with the MS^{DM} index, but uncorrelated with the misvaluation measures and error terms. The reviewed positive and significant effect of the MS^{DM} index in models 1 and 4 for the two-stage least square regressions is not affected by an endogeneity problem. Similarly, the effects of margin trading and short selling on stock misvaluation continue to hold in the two-stage least squares regression.

Table 3.10. Endogeneity check

Panel A: Dynamic GMM

	(1) MSVF	(2) MSVF	(3) MSVF	(4) $MSVF_{Chang}$	(5) $MSVF_{Chang}$	(6) $MSVF_{Chang}$
Variables						
Intercept	-1.453***	-1.455***	-0.571***	-1.512***	-1.512***	-2.21***
	[-20.3]	[-20.02]	[-7.69]	[-28.29]	[-28.29]	[-18.54]
Dep_{-2}	0.274***	0.279***	0.265***	0.264***	0.264***	0.129***
	[33.47]	[37.08]	[30.16]	[51.63]	[51.64]	[14.61]
Dep_{-1}	0.544***	0.543***	0.652***	0.444***	0.444***	0.404***
	[80.63]	[76.6]	[83.07]	[106.92]	[107.03]	[35.19]
MS_{-1}^{DM}	1.352***			0.452***		
	[9.3]			[4.94]		
MT_{-1}		1.38***			0.441***	
		[9.32]			[4.84]	
SS_{-1}			-124.57***			-181.782***
			[-3.42]			[-2.61]
Lev	-0.204***	-0.192***	-0.136***	0.146***	0.147***	0.338***
	[-6.37]	[-6.55]	[-5.59]	[8.83]	[8.86]	[7.73]
Profitability	-2.201***	-2.186***	-1.886***	-2.073***	-2.073***	-3.441***
	[-34.35]	[-28.26]	[-21.2]	[-57.4]	[-57.35]	[-24.97]
CapEx	0.075***	0.074***	0.025***	0.063***	0.063***	0.082***
	[20.92]	[20.98]	[7.39]	[22.82]	[22.81]	[15.14]
Market-to-Book	0.016***	0.016***	0.013***	0.039***	0.039***	0.076***
	[20.97]	[21.59]	[10.29]	[70.1]	[70.03]	[34.83]
Volatility	0.141	0.084	4.775***	-1.647***	-1.654***	1.276***
	[0.66]	[0.38]	[20.09]	[-12.9]	[-12.97]	[3.4]
Analyst Coverage	0.01***	0.01***	0.012***	0.009***	0.009***	0.025***
	[17.4]	[18.5]	[8.66]	[75.92]	[76.07]	[19.56]
Obs.	24505	24505	24505	33906	33906	33906
Durbin-Waston	2.059	2.058	2.024	2.030	2.030	2.015
AR(2) p-value	0.668	0.558	0.816	0.441	0.436	0.409

Panel B TSLS

	(1) MSVF	(2) MSVF	(3) MSVF	(4) $MSVF_{Chang}$	(5) $MSVF_{Chang}$	(6) $MSVF_{Chang}$
Intercept	-0.115***	-0.116***	-0.115***	-0.088***	-0.088***	-0.097***
	[-13.35]	[-13.39]	[-13.87]	[-10.84]	[-10.84]	[-11.62]
Dep_{-1}	0.974***	0.974***	0.932***	0.934***	0.934***	0.935***
	[648.59]	[648.93]	[682.2]	[733.67]	[733.71]	[719.16]
MS_{-1}^{DM}	0.392**			1.044***		
	[2.35]			[10.3]		
MT_{-1}		0.244**			1.026***	
		[2.26]			[10.13]	
SS_{-1}			-69.508***			-97.083***
			[-8.39]			[-11.7]
Lev	-0.001	-0.001	-0.001	-0.007**	-0.007**	-0.007**
	[-0.27]	[-0.25]	[-0.4]	[-2.3]	[-2.29]	[-2.07]
Profitability	-0.005	-0.005	-0.015**	-0.027***	-0.027***	-0.026***
	[-0.65]	[-0.64]	[-2.11]	[-3.96]	[-3.96]	[-3.65]
CapEx	0.003***	0.003***	0.004***	0.002***	0.002***	0.003***
	[7.65]	[7.65]	[8.63]	[6.1]	[6.1]	[6.56]
Market-to-Book	0.001***	0.001***	0***	0.001***	0.001***	0.001***
	[26.89]	[26.96]	[19.52]	[27.02]	[27.02]	[26.43]
Volatility	2.03***	2.039***	2.141***	2.266***	2.266***	2.371***
	[36.44]	[36.89]	[40.17]	[43.08]	[43.08]	[43.97]
Analyst Coverage	0.003***	0.003***	0.003***	0.002***	0.002***	0.002***
	[18.23]	[18.25]	[15.25]	[12.02]	[12.01]	[12.35]
Obs.	64220	64220	64220	64220	64220	64220
Adj.R square	89.18%	89.19%	89.98%	91.56%	91.56%	91.20%

Notes: This table shows the Dynamic Panel GMM regression and two-stage least square regression results of an eligible firm lagged MS^{DM} index on misvaluation measures. The dependent variables are the misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). In Panel A, models 1 and 2 present the dynamic DMM estimations. In Panel B, the lagged MS^{DM} index, MT, and SS are instrumental with the respective industry mean in two-stage least squares regression. Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

To address the concern that our finding is subject to the chosen misvaluation measures, we use an alternative misvaluation measure. We follow Ohlson (1995) to compute stock misvaluation from a residual income model. Compared with the misvaluation measure of

Rhodes-Kropf et al. (2005) and Chang et al. (2013), the misvaluation of Ohlson (1995) is a forward-looking approach[33] that discounts forecasted information.

Table 3.11 reports the results based on Ohlson (1995)'s misvaluation measure. From the table, the coefficient of $\mathrm{MS^{DM}}$ index is still positive and significant on $\mathrm{MSVF_{Ohlson}}$. The result is consistent with and without the past misvaluation measure ($\mathrm{Dep_{-1}}$). The higher the $\mathrm{MS^{DM}}$ index, the more serious the stock misvaluation. Moreover, margin trading is positively associated with $\mathrm{MSVF_{Ohlson}}$, while short selling negatively affects $\mathrm{MSVF_{Ohlson}}$. Margin trading enhances stock misvaluation. In contrast, short sales mitigate the misvaluation. These findings are consistent with our main findings in Table 3.5. Hence, using an alternative misvaluation measure does not alter our findings.

Table 3.11. Alternative misvaluation measure of Ohlson (1995)

Variables	(1) MSVF_{Ohlson}	(2) MSVF_{Ohlson}	(3) MSVF_{Ohlson}	(4) MSVF_{Ohlson}	(5) MSVF_{Ohlson}
Constant	0.431***	4.411***	49.851***	4.703***	4.104**
	[23.49]	[2.69]	[9.27]	[2.83]	[2.45]
$\mathrm{Dep_{-1}}$	0.811***	0.79***		0.791***	0.795***
	[60.14]	[53.16]		[50.88]	[50.39]
$\mathrm{MS^{DM}_{-1}}$	37.925***	34.994***	53.981***		
	[6.64]	[5.96]	[6.01]		
$\mathrm{MT_{-1}}$				35.9***	
				[6.32]	
$\mathrm{SS_{-1}}$					-145.719***
					[-3.02]
Lev		0.209	0.64	0.251	0.1
		[0.37]	[0.33]	[0.44]	[0.17]
Profitability		0.833	-3.839	1.561	1.861*
		[0.85]	[-1.48]	[1.54]	[1.78]
CapEx		-0.244***	-2.544***	-0.233***	-0.209***
		[-2.97]	[-9.5]	[-2.95]	[-2.64]
Market-to-Book		0.039**	0.107	0.044**	0.048**
		[2.21]	[1.5]	[2.05]	[2.08]
Volatility		6.748	26.923***	-3.822	-3.214
		[1.52]	[3.83]	[-0.81]	[-0.66]
Analyst Coverage		-0.029***	-0.052***	-0.016***	-0.015***

[33] We report the construction process of the misvaluation measure of Ohlson (1995) in Appendix A.1.

		[-4.04]	[-3.67]	[-3.73]	[-3.34]
Obs.	6556	6550	6551	6550	6550
R-square	82.13%	82.47%	48.03%	82.47%	82.21%

Notes: This table reports the fixed effect estimations of the effect of an eligible firm's lagged MS^{DM} index on the misvaluation measure of Ohlson (1995). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

3.7. Conclusion

This chapter investigates the effect of imbalanced trades between margin trading and short selling on stock misvaluation in the Chinese stock market where the pilot programme provides us an ideal experimental laboratory to conduct such analysis. First, we find a positive effect of the MS^{DM} index (margin-trading activities) on stock misvaluation. Second, we classify firms into over- and undervalued groups to investigate the effect of MS on extremely mispriced firms. We find that imbalanced trades escalate firms' overvaluation but reduce the extent of undervaluation. Third, the positive effect of MS on misvaluation holds for both bull and bear markets. Fourth, we find that recent-year trades in the Chinese pilot programme mitigate the relationship between the imbalanced trades of margin traders and short sellers. Moreover, we find that margin trading mainly contributes to the effect of the MS^{DM} index on misvaluation. Margin-trading activities not only expand the overvaluation but also correct the undervaluation. We argue that margin traders are information conveyors. In contrast, short-selling activities reduce stock misvaluation, especially having a stabilising function during bull markets. Furthermore, the dynamic panel DMM regression and the two-stage least squares regression provide robustness support for our results. Our findings remain the same using the alternative misvaluation measure.

This chapter contributes to the literature by expanding the research related to the effect on asset pricing of lifting the ban on margin trading and short selling in the Chinese stock market. We attempt to fulfil the research gap remaining following the research of Chang et al.

(2014), that the effect of margin trading on price efficiency is ambiguous. We argue that margin trades escalate overvaluation and reduce undervaluation. Moreover, the existing literature finds that lifting the ban on short selling improves price efficiency through incorporating more negative information into stock prices. We focus on the combined trading effect of margin traders and short sellers and uncover that imbalanced trades positively affect stock misvaluation.

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CHAPTER FOUR

Stock Misvaluation and ESG: Evidence from China A-share Stock Market

ESSAY THREE

This chapter presents the third essay, which investigates the relationship between ESG performance and stock misvaluation in the Chinese stock market. The chapter is organised as follows. Section 4.1 introduces the background and key findings. Section 4.2 reviews the related literature. Section 4.3 presents the methodology and data sample. Section 4.4 shows the main results and related analysis. Section 4.5 performs the robustness check. Section 4.6 concludes the third essay.

4.1. Introduction

Climate change and carbon control, together with various types of sustainable development initiatives, have received increasing attention from investors, firms' stakeholders and academics over the past two decades. In order to meet the requirements of various stakeholders and regulatory authorities, firms are required to disclose more non-financial information encompassing the environmental, social and governance aspects. A firm's ESG (environment, social and governance) practices are important, as they affect not only a firm's ability to attract investors and raise capital but also the information source investors have access to. Investors who prioritise ESG considerations may be attracted to firms with eco-friendliness, high social standards and prudent governance, and are more likely to buy these firms' shares. Conversely, an opposing perspective applies. Firms' engagement in ESG practices may, in some cases, come at the cost of overall firm misvaluation, which encroaches upon shareholder profits. This raises the need to examine the relationship between ESG performance and firm valuation.

Traditional financial theories provide conflicting perspectives regarding the effect of ESG performance on firm value. The shareholder primacy theory proposed by Friedman (1970) asserts that the only goal of firms is to maximise the profits of shareholders. However, the principle-agency problem arising from the separation of ownership and management likely creates opportunities for managers to pursue personal gains or good reputations through engaging in ESG practices which may harm the firm value (Nekhili et al., 2021). The view is held by the stakeholder theory posits that firms should be responsible for various stakeholders, including employees, managers, customers and society, among other interested groups (Freeman, 2010). Firms with ESG development as a social responsibility behaviour can enhance employee recognition and improve products' competitiveness (Hur et al., 2018). These theories have implications for misvaluation, which are elaborated on below.

As implied by above-mentioned theories, a firm's ESG performance not only affects its value but also may impact firm valuation. Investors who prioritise ESG considerations may tend to value more highly firms with better ESG performance. On the one hand, from an investment perspective, the ESG preference changes investors' beliefs when making investment decisions. Even during a period when the price of stocks with good ESG performance experience a decline, these investors are less likely to sell their stocks (Starks et al., 2017). These investors focus more on ESG performance and react less to the direct signals of firm value. (Cao et al., 2021). This possibility would lead to a drift of the firm value from its intrinsic value, hence creating stock misvaluation. On the other hand, from the view of information availability, a firm's ESG disclosure expands the information sources for investors, facilitating a more accurate valuation of the stocks through enhanced information transparency. Kim et al. (2012) advocate that firms with better ESG performance tend to release more ESG-related information to the public. Thus, firms with higher ESG scores may have less stock misvaluation and, hence, higher price efficiency.

The Chinese stock market provides an ideal setting for investigating the impact of ESG performance on stock misvaluation. First, the ESG development in China is largely driven by government policy. The Chinese government[34] aims to achieve carbon neutrality by 2060, with an interim objective of reaching the carbon peak in 2030. Although China started its ESG endeavours later than the European and US markets, its progress has been swift. Chinese firms started to disclose environment and sustainable development information in their social responsibility reports in 2008 to enhance their competitive advantage (Albuquerque et al., 2019). The number of reports has increased from an initial 32 to 2023 over the period spanning from 2006 to 2019. Second, in contrast with the mandatory disclosure in the European market,

[34] This information is sourced from the official website of the National Development and Reform Commission of China. https://www.ndrc.gov.cn/wsdwhfz/202111/t20211111_1303691_ext.html

the China Securities Regulatory Commission (CSRC) advocates a voluntary ESG disclosure, with the exception of heavily-polluted firms, which are required to disclose environmental information. In contrast to the mandatory ESG disclosure policy in some markets, the voluntary nature of ESG disclosure shows firms' willingness and motivations to release non-financial information to public. Third, the composition of Chinese investors is different from developed markets. The Chinese stock market is dominated by individual investors who may not possess a strong understanding of ESG investment principles, due to their lack of professional knowledge and trading skills. Prior literature focuses on the impact of ESG performance on firms' valuation in developed markets. However, few studies investigate whether the ESG score leads to stock misvaluation in developing markets.

In this chapter, we investigate whether the ESG performance of firms leads to stock misvaluation and, thus, affects the market efficiency in the Chinese stock market. We carry out our examination by investigating value effects across the three distinct dimensions of ESG; environmental (E), social (S), and governance (G). It is important to analyse these pillars separately, as each measure different facets of these firms' performances.

We find that the ESG score negatively and significantly impacts stock misvaluation. We also find a negative impact of the G score on misvaluation. This negative relationship emerges from the fact that the G score will reduce the overvaluation and undervaluation. In other words, better corporate governance helps to correct stock misvaluation, driving a firm's value towards the intrinsic value. Conversely, the S score positively impacts the overvaluation. The opposite signs of the coefficients on the S score and the G score explain the insignificance of the coefficients on the ESG score for both, either overvaluation or undervaluation. This finding underscores the importance of investigating the environmental, social and governance performance of firms separately. In summary, our results indicate that the ESG score affects stock misvaluation, especially the G score, which corrects stock misvaluation.

The existing literature shows that ESG engagement enhances information availability (Lopatta et al., 2015; Siew et al., 2016; Cui et al., 2018). We examine whether the information availability can influence the relationship between the ESG score and stock misvaluation. We use the ESG disclosure score to measure information availability. The ESG disclosure score measures the extent of ESG information that a firm publicly discloses, rather than the ESG performance per *se*. A high value for the ESG disclosure score indicates more non-financial information availability for a firm and vice versa. We find that the ESG disclosure score positively influences the relationship between ESG and misvaluation.

We also examine whether the relationship between ESG and misvaluation is affected by macroeconomic conditions. During periods of high uncertainty, firms may enhance their overall ESG performance by viewing ESG practices as risk-reduction measures (Vural-Yavaş, 2021). In this chapter, we examine the effect of economic policy uncertainty (EPU) shock on stock misvaluation. We find no evidence that the relationship between ESG and misvaluation is affected by EPU.

Our findings hold for robustness checks. First, to reduce the concern of data bias raised from the choice of ESG score, we use the ESG score from different data providers and find the negative effects of the ESG score and the G score on misvaluation remain unchanged. Second, we tackle the industry bias through excluding the financial firms and using the industry-adjusted ESG score. Third, to mitigate the endogeneity concern, we use two-stage least squares regression with the mean value of the ESG (E,S,G) score for each industry as the instrumental variable and the dynamic GMM regression to examine the relationship between ESG and misvaluation. We find that the negative and significant signs on the ESG score and the G score remain robust.

This chapter contributes to the literature in the following three aspects. First, while previous literature focuses on examining the impact of ESG performance on firm performance and firm value, showing that ESG is positively associated with firm value. There has been limited investigation on the relationship between the ESG performance and price efficiency, especially in the developing market. To the best of our knowledge, we are the first to investigate how ESG performance influences stock misvaluation in the Chinese stock market. We document a negative relationship between the ESG performance and misvaluation measure and, hence, posit that ESG performance does influence stock misvaluation. Second, we extend the ESG-related literature to analyse the value effect of the three pillars of ESG. We find that the G score corrects stock misvaluation, while a higher S score leads to overvaluation. We do not find any significant effect on the environmental performance of firms. The different signs on the coefficients of the three dimensions of ESG suggest that researchers should analyse the ESG issue separately for each pillar, as each pillar measures different angles of firms' performance. Third, we find the ESG (G) disclosure score can influence the relationship between ESG (G) score and misvaluation. This finding indirectly supports our main findings. The negative effect of ESG (G) performance on stock misvaluation may be derived from the information availability.

4.2. Literature Review

4.2.1. Two Opposite Theories

The ESG score contains the nonfinancial information of a company's engagement in socially responsible investment and sustainable development. Implementing ESG practices may lead to better stakeholder engagement (Eccles et al., 2014), as well as increasing nonfinancial information transparency (He et al., 2022). Previous literature has documented that ESG performance could affect firm value (Ding et al., 2016; Huang et al., 2020). However, there is no consensus regarding whether a better ESG performance could enhance/reduce firm value. Shareholder primacy theory and stakeholder theory provide opposite theoretical predictions for the relationship between ESG performance and firm value.

According to shareholder primacy theory, firms' ESG engagement may damage their market value. Friedman (1970) seeds the shareholder primacy theory showing that maximising shareholders' profits is the only goal of companies. In fact, moral hazard problems associated with the separation of ownership and management rights lead to interest conflict between owners and managers. Managers, under pressure from ESG investors and their desire to build a positive reputation, are motivated to actively participate in environmental protection practices and social responsibility programmes. In doing so, they may violate the core responsibilities of protecting shareholders' interests and rights, as they probably engage in non-profit programmes at the cost of firms' profits (Friedman, 2007). Developing ESG businesses may also leave managers to seek their personal interests (Nekhili et al., 2021). They pursue, for example, a career promotion opportunity through involvement in socially responsible businesses.

Excepting the managers' role in the relation between ESG and firm value, implementing ESG practises can also damage firm value from other aspects. Increasing numbers of consumers prefer products with green labels, which drives companies to purse ESG programmes. Firms may expend efforts on advertising and marketing to create an illusion of corporate social responsibility, all the while minimising their actual engagement in actions. This practice is commonly referred as greenwashing. Even though some firms have strong ambitions to invest in ESG business, low ESG performances may have detrimental effects on firms' reputations (Aouadi & Marsat, 2018; Fatemi et al., 2018). In addition, firms may incur additional costs for disclosing non-financial information (Lin et al., 2021). Based on shareholder primacy theory, implementing ESG practises could damage firm value, reflecting a negative relationship between ESG performance and firm value.

Stakeholder theory provides an opposite view to shareholder primacy theory, holding that companies are responsible for all stakeholders' interests (Freeman, 1984). According to stakeholder theory, companies should take social responsibility for all stakeholders rather than solely the interests of company owners. These stakeholders involve managers, employees, customers, suppliers, society, environment and creditors, among other stakeholders (Freeman, 2010). Based on stakeholder theory, companies tend to keep committing to corporate social responsibility business practices even during a market downturn or when facing a downturned business cycle. This commitment arises from the recognition that developing an environmental, social and governance (ESG) programme is a way for companies to fulfil their responsibility to all stakeholders. Implementing ESG practices could help firms improve value, implying a positive relation between ESG performance and firm value.

Firms engaging in ESG practices could benefit their stakeholders. Hur et al. (2018) state that firms with social responsibility behaviour could increase employee recognition and motivate employees to improve productivity, thereby improving the competitive advantage of the firm's products. Sanchez (2000) also shows that it could help establish a stable customer relationship and gain the government's trust, which would ultimately increase the market share of these firms and increase their firm value. Moreover, He et al. (2022) examine the effect of ESG performance on executive managers of companies and show that firms' ESG performance could inhibit managers' misconduct. Their finding supports that better ESG performance of firms attracts the attention of analysts and brokers who deliver external monitoring pressure to promote the self-discipline of managers.

4.2.2. ESG and Firm Valuation

Recent literature tends to empirically investigate the effect of ESG engagement on firm value and performance (for example, Fatemi et al., 2015; Fatemi et al., 2018). Fatemi et al. (2015) document that a firm's expenditure associated with ESG creates firm value. However, few studies investigate how ESG affects stock misvaluation and, thus, affects market efficiency. Investors with ESG preferences may change their investment decisions because an updated belief of investors changes the expectation of future returns (Baker & Wurgler, 2006; Serafeim, 2020; Cornell, 2021). Social responsibility institutions are less likely to react to firm value changes, but focus on ESG performance (Cao et al., 2021). This means that institutions with an ESG preference are more likely to buy overvalued stocks and sell undervalued stocks than institutions without an ESG preference, as institutions with an ESG preference focus more on ESG performance than a valuation signal. This implies a departure of the firm market value and intrinsic value. Moreover, investors with an ESG preference tend to hold "green" stocks when these stocks experience a poor performance period, because they believe that a long-term value created by the ESG engagement would ultimately offset the short-term loss (Starks et al., 2017). In other words, investors with ESG preferences are less sensitive to the signal of firm valuation, creating a possibility of stock misvaluation.

One stream of literature provides some indications on a positive sign of ESG score on overvaluation. A halo effect suggested by Hong and Liskovich (2015) implies that higher ESG performance may lead to higher stock misvaluation. This effect derived from the cognition of human beings shows that the overall impression by people of a firm could affect the way they judge the firm (Nisbett & Wilson, 1977). Consumers may be more likely to pay for "environmentally-friendly" products to express their willingness to adapt to climate change and support sustainable development. Investors may perceive this effect and tend to have more willingness to value firms with high ESG performance. Moreover, investors increase the amount of capital to sustainable initiatives that are gaining popularity, resulting in a possibility of overvaluation. Bofinger et al. (2022) find a positive effect of the ESG score on the misvaluation measure for the US market. In detail, the ESG score expands the stock overvaluation while reducing the existing undervaluation. Their findings support stakeholder theory, suggesting that investors value more for high ESG-scored firms. In addition, Zhang et al. (2021) find that US firms engaging in ESG practices provide value protection against the adverse events by improving the firm's Tobin Q value.

Another stream of literature argues that ESG practices increase information availability (Lopatta et al., 2015; Siew et al., 2016; Rossi & Harjoto, 2020). Firms with ESG practices may decrease stock misvaluation, as investors are more likely to properly value stocks when information transparency increases. Different from accounting information reporting in financial statements, firms disclose ESG information in annual reports or CSR reports. Although the disclosure requirements of ESG information varies across countries, most countries encourage firms to provide ESG information. In many developed markets, such as the European markets, disclosing ESG information is mandatory for companies.

From the view of information transparency, firms' ESG practices may improve price efficiency and, therefore, reduce stock misvaluation. Modigliani and Miller (1963) proposed that investors have the same information set when they forecast future stock returns. However, this view is challenged by reality and following researchers. Managers better know their own firms' ESG engagement than outsiders. Hence, improving information transparency of firms is a good way to reduce the information asymmetry between insiders and outsiders, and help market participants fairly price stocks. Byard et al. (2006) find that better disclosure and higher transparency of ESG, oriented from the strong corporate governance, could enhance investors' ability to arbitrage pricing errors and properly value stock. They argue that an effective and independent board tends to improve financial and operational transparency, giving directors a strong motivation to function better as a watchdog on daily business on behalf of shareholders. Hence, investors could correct stock misvaluation more quickly in these stocks with higher transparency. This opinion is supported by Wong and Zhang (2022), who argue that ESG information disclosure provides nonfinancial information of firms to the capital market, where traders could utilise this information set to more precisely value stocks and alleviate price delays from information asymmetry. He et al. (2022) advocate that ESG information could also complement the financial information of firms and, thus, improve the transparency level of firm information. Moreover, Cui et al. (2018) find that the ESG information disclosure decreases information asymmetry. As the quality of ESG information improves, the biases of earnings forecasts will be driven down, hence improving market efficiency (Becchetti et al., 2013). In addition, Kim et al. (2014) provide a view of ESG implications on price efficiency from the stock crash. They find that a firm's ESG performance is negatively associated with the stock crash risk, because firms with better quality ESG have higher information transparency and timely release of information to market participants and, thus, reduce managers' hoarding behaviours to accumulate bad news.

Three main dimensions of ESG may also affect stock misvaluation. Environmental information disclosure, and the performance of companies as part of ESG, have received more and more attention (Xu et al., 2021). Zhang and Yang (2023) show that environmental information can reduce the price delay and, thus, improve price efficiency. Environmental information helps investors make investment decisions by providing important characteristic information about firms, because investors can interpret firm development strategies from an environmental perspective (Xu et al., 2021). Similarly, Gong et al. (2019) show that stocks with ESG engagement have good pricing efficiency performance in terms of information reaction speed. They also find that social information of firms reduces the price delay. Moreover, a high quality of corporate governance could lead to higher price efficiency (Lee et al., 2016). They argue that effective corporate governance can enhance the timely delivery of valuable information to investors by diminishing both the motivation and capacity of managers to conceal such information. This is particularly crucial as managers may sometimes to be inclined to prioritise their self-interest.

4.2.3. Chinese Stock Market

More and more Chinese firms start to publicly disclose ESG information in social responsibility reports following a regulation change in 2008[35] (He et al., 2022). From the perspective of information disclosure, the increasing ESG information helps investors reduce earnings forecast errors and biases by reducing the information asymmetry (Lee et al., 2016), therefore reducing stock misvaluation. The Chinese government encourages firms to disclose ESG information to adapt to sustainable development and climate-changing requirements, and firms voluntarily provide nonfinancial information (Ong & Han, 2019). In contrast with the mandatory disclosure requirement of European markets, the voluntary disclosure of ESG information could reflect the willingness of firms to disclose ESG information to investors and, therefore, improve price efficiency through enhancing information transparency. Hence, there may be a negative impact of the ESG score on stock misvaluation in the Chinese stock market.

However, the possible negative effect of ESG performance on the Chinese stock misvaluation may be challenged by the following arguments. First, many firms do not publicly disclose ESG information and, hence, reduce the information availability (Raimo et al., 2021). Second, non-mandatory disclosure provides chances for companies to disclose good ESG performance for releasing “good news” to market participants (Kim et al., 2012). This will lead to lagged information to investors who use it to make investment decisions and cause stock

[35] The social responsibility report (CSR report) was renamed the ESG report in 2018 in China.

misvaluation. Third, the Chinese ESG programme is in a comparatively initial stage where the government encourages the market to develop ESG. To cater to market and customers' demands, companies may engage in greenwashing activities by overstating their ESG plans while minimising the actual engagement (Falcao et al., 2020). Moreover, the non-unified standard would leave space for firms to develop low-quality ESG information and may mislead investors. According to Darnall et al. (2022), the intensity and form of ESG reporting varies across firms. Either low-quality ESG information or greenwashing behaviour by firms will frustrate investors when they collect and analyse ESG information, leading to a gap between the expected value and the true value of a firm.

4.2.4. Motivations of ESG Information Disclosure

Different motivations for ESG disclosure determine different ESG effects on firm valuation. Firms face an adverse selection issue when they report ESG activities. Under the voluntary disclosure framework, firms with good ESG performance tend to extensively report ESG-related information, while firms with poor ESG performance are more likely to report it minimally (Verrecchia, 1983; Dye, 1985). This argument is confirmed by Cahan et al. (2015), who show that firms with positive ESG performance have higher firm value. Moreover, firms can manage public perception through ESG disclosure. Cho and Patten (2007) show that firms may explain the changes in ESG policies to reduce the adverse impact raised by environmental damage on firm market value. Additionally, managers have intentions to hide ESG information from the public, when they perceive this information as being harmful and costly to their profits.

4.2.5. Macroeconomic Movement

The economic policy uncertainty (EPU) index could be a sound measure of the macroeconomic uncertainty movement, which is a good measure to examine its role in the relationship between the ESG score and firm valuation. Vural-Yavaş (2021) states that firms perceive ESG practice as risk-reducing activities and increase ESG performance during periods of high uncertainty. Moreover, Hwang et al. (2021) find that firms with higher ESG performance experience a smaller earnings decline, suggesting that the non-financial information is useful for investors to make investment decisions in relation to high market uncertainty. Their finding provides support for ESG, serving as a buffer for a firm's value during an uncertain period, which evokes a negative sentiment among investors. Engelhardt et al. (2021) also find that high ESG-rated firms have higher abnormal returns with lower volatility in the European stock market.

4.3. Methodology and Data Sample

4.3.1. Methodology

To examine the relationship between ESG and stock misvaluation, we apply a fixed effect panel regression[36] model to our panel data (Ding et al., 2016; Cui et al., 2018; Bofinger et al., 2022). This model allows unobserved variables to have correlations with the observed variables. In other words, it treats the unobserved variables as fixed parameters. To alleviate the issue of autocorrelation in the residual, we augment our regression model by including the one-year lagged dependent variable as an additional control variable. Stock misvaluation may be persistent in continuous periods (Avramov et al., 2020). Incorporating the one-year lagged

[36] The p-values of the F-test for all fixed effects panel regressions in Essay Three are less than 0.001. The significant p-value indicates that the fixed effects panel regression model is more suitable than the OLS regression model in our data sample, as the fixed effect is significant. We do not report this figure in tables for concise.

dependent variable could reduce the concern that the relationship between misvaluation and ESG is driven by past stock misvaluation. Moreover, incorporating the past stock misvaluation as an additional variable can reduce the reverse causality presented by Bofinger et al. (2022), who advocate that stock misvaluation may affect a firm's ESG performance. Specifically, overvalued firms may find it easier to access financing, enabling them to engage more actively in ESG activities. The benchmark regression is denoted as:

$$y_{i,t} = \beta_0 + \beta_1 \mathrm{Dep}_{i,t-1} + \beta_2 ESG_{i,t-1} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{4.1}$$

$y_{i,t}$ is the dependent variable defined as the stock misvaluation[37]. $\mathrm{Dep}_{i,t-1}$ is the one-year lagged misvaluation value. Hence, β_1 captures the effect of past stock misvaluation on the current value. $ESG_{i,t-1}$ is the one-year lagged ESG score of a firm. β_2 captures the impact of lagged ESG performance on stock misvaluation. $X_{i,t}$ is a series of control variables. β_3 is a vector of betas representing the effects of the controls on stock misvaluation.

We take a further look at the effects of the three dimensions of ESG on stock misvaluation, as each represents a specific facet of a firm's engagement in sustainable development and social responsibility. It is important to note that firms may excel in one ESG dimension while not performing as well in another, as evidenced by Bissoondoyal-Bheenick et al., (2023). Hence, we examine the three main dimensions of ESG separately and replace the target variable ESG score with the E score, the S score and the G score in equation (4.1). We then present the regression equations as follows:

[37] The misvaluation measure is generated from modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), considering ownership classification in the benchmark regressions.

$$y_{i,t} = \beta_0 + \beta_1 \mathrm{Dep}_{i,t-1} + \beta_2 E_{i,t-1} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{4.2}$$

$$y_{i,t} = \beta_0 + \beta_1 \mathrm{Dep}_{i,t-1} + \beta_2 S_{i,t-1} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{4.3}$$

$$y_{i,t} = \beta_0 + \beta_1 \mathrm{Dep}_{i,t-1} + \beta_2 G_{i,t-1} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{4.4}$$

4.3.2. Variables Description

Dependent variable and control variables

We use stock misvaluation (MSVF) as the dependent variable. The construction of MSVF has been given in Section 2.3.1. A variety of control variables are the leverage ratio (Lev), profitability (Profitability), capital expenditure (CapEx), market-to-book ratio (Market-to-Book), analyst coverage (Analyst Coverage), and the volatility of stock returns (Volatility), as presented in Chapter Three. The definition of the control variables is shown in Section 3.4.3.

Main explanatory variables

The main explanatory variables are ESG score, E score, S score and G score, denoted as $ESG_{i,t-1}$, $E_{i,t-1}$, $S_{i,t-1}$, and $G_{i,t-1}$, respectively. These variables collectively provide a comprehensive assessment of a firm's sustainable development performances. A detailed description of the main variables is shown in Section 4.3.3. ESG, being non-financial information, is subject to different disclosure requirements compared to a firm's accounting data. Most firms disclose ESG information in their annual reports, which are publicly reported later than their financial statements. Hence, we follow Bofinger et al. (2022) and take a one-year lag for the target variables to reflect the fact that investors obtain information about a firm's ESG performance after the company's fiscal year.

Information transparency variables

Prior literature shows that the impact of ESG on stock price efficiency may be affected by information availability (Lopatta et al., 2015; Siew et al., 2016; Cui et al., 2018). To examine whether there are factors affecting the ESG-misvaluation relationship, we carefully consider possible variables identified in the existing literature. We include four measures of information asymmetry based on Bofinger et al. (2022) and the ESG disclosure score (Fatemi et al., 2018), which measures the extent to which firms disclose their ESG information publicly. The former captures the information asymmetry, while the latter measures information transparency. Both measures reflect two different perspectives of information availability. We provide details of the ESG disclosure scores in Section 4.3.3.

We use four information asymmetry measures that are well documented in the literature, including the earnings forecast error, earnings standard deviation, illiquidity and bid-ask spread. The earnings forecast error measures the deviation of the mean of all analysts' earnings forecasts from the actual reported earnings per share in the respective fiscal year (Krishnaswami & Subramaniam, 1999). A high earnings forecast error indicates a dearth of information. The earnings standard deviation represents the standard deviation of all analysts' earnings forecasts at the fiscal year end. It measures the variance in consensus estimates among analysts (Krishnaswami & Subramaniam, 1999). A high earnings standard deviation indicates high information asymmetry, because of stronger disagreement among analysts. Illiquidity[38] is defined as the mean value of the daily absolute returns divided by the trading values in each year (Amihud, 2002). It reflects investors' ability to trade stock without impacting prices. A higher Illiquidity measure indicates a larger amount of information asymmetry. The bid-ask spread is measured as the mean value of the daily bid-ask spread in each year (Silber, 2005).

[38] To facilitate ease of understanding by readers, illiquidity is multiplied by 10 million to reflect the percentage-return change of ￥10 million trading value.

The spread is calculated as (ask - bid)/((ask + bid)/2). The wider the bid-ask spread, the stronger the information asymmetry.

4.3.3. Data Description

Our research sample includes all Chinese A-share companies listed in the Shanghai and Shenzhen stock markets from 2009 to 2020. The accounting data is obtained from the China Stock Market & Accounting Research (CSMAR) database. The ESG data are sourced from the Huazheng and Wind databases. We use Huazheng ESG data in our main analyses due to its extensive coverage of Chinese firm-level ESG performance over the longest historical period available among well-known databases[39]. The data sample commences at the earliest point where ESG data is accessible. The long enough period of time-series ESG data enables us to investigate the ESG impact on stock misvaluation. To address concerns related to un-unified ESG standards and potential disparities of ESG ratings across ESG data providers, we use Wind ESG for the robustness check. Excluding Huazheng ESG, Wind ESG encompasses the most extensive range of firm observations, to the best of our knowledge. In addition, we acquire earnings forecast information from Refinitiv I/B/E/S.

Our ESG dataset includes both the score and ratings which measure firms' ESG performance. The ESG score ranges from 1 to 100, where 100 represents the best ESG performance. A nine-tier rating is also given to a scored firm, ranging from "CCC to AAA". The ESG rate may capture investors' attention, as it is more intuitive for investors to understand and make it easier to compare the ESG performance of different firms. Both ESG score and the

[39] We compare ESG firm-year observations from various sources including Bloomberg, MSCI, FTSE, Refinitiv, SynTao Green Finance, Huazheng and Wind. We find that Huazheng ESG performance data offer the most extensive coverage, spanning the longest period. Huazheng ESG data is provided by Sino-Securities Index Information Services (Shanghai) Co. Ltd. which is an independent third-party organisation primarily serving asset management institutions.

ratings are categorised into three main dimensions; (the environmental, social and governance pillars) to reflect specific filings of a firm's ESG-related performance. Each of three dimensions share the same scoring and rating system as the overall ESG classification. The detailed ESG data enables us to investigate not only the collective impact of ESG on stock misvaluation, but also the effect from each particular dimension of ESG.

To investigate the influencing role of variables in the ESG-misvaluation relationship, we obtain ESG, E, S and G disclosure scores data from Bloomberg. The Bloomberg ESG (E,S,G) disclosure score is derived from the extent to which a firm discloses its environmental, social and governance (ESG) information to the public. This disclosure score ranges from 0 to 100, representing the degree of ESG information disclosed by firms. A score of 0 means that a firm does not disclose ESG information at all, while a score of 100 indicates a full reporting of all ESG data. Unlike the ESG score which measures a firm's ESG performance, the ESG disclosure score measures the amount of ESG data a firm publishes publicly which reflects information transparency. We report the summary statistics of both the ESG score and the ESG disclosure score in Table 4.1.

4.4. Results

4.4.1. Summary Statistics

Table 4.1 shows the summary statistics of variables used in this chapter, including the number of firm-year observations, mean, median, the standard deviation, the first quartile and third quartile, and the minimum and maximum values. We winsorize all variables at the 1% and 99% percentiles. The mean value of stock misvaluation (MSVF) is close to zero, with a standard deviation of 0.7. The mean value of the ESG score[40] is 72.9. For the three pillars of the ESG score, the E score has the lowest mean value of 59.99 and median value of 59.69. In contrast, the G score has the highest mean and median value, which are 79.13 and 80.9, respectively. The different performance of the ESG pillars show that Chinese companies have better corporate governance than environmental performance under the ESG scoring framework. Similarly, Chinese companies have sounder governance (G) disclosure systems than their environmental (E) disclosure. The mean value of the G disclosure score is much higher than the E and S disclosure scores. Moreover, the average value of the ESG disclosure score is 24.56, indicating that many Chinese companies do not have so much willingness to publicly disclose their ESG-related information.

Figure 4.1 shows the ESG (E, S, G) rating distribution, as well as the mean value of MSVF on the ESG rating. In this figure, the ESG, S and G ratings of firms are close to the normal distribution, except for the distribution of the E rating, which is heavily right-skewed. This finding implies that the majority of ESG ratings of Chinese firms belong to the "Average" level"[41], indicating that Chinese firms need to improve their environmental performance. The right-skewed distribution of the E score matches the relatively low mean value of the E score in Table 4.1. In addition, the varying mean value of MSVF across the ESG rating indicates that firms with extremely low and high ESG ratings (left and right) tend to be the most overvalued, and average-rating firms tend to be fairly valued.

[40] The ESG (E, S, G) score and ESG (E, S, G) disclosure score are reported as raw data in Table 4.1. They are divided by 100 to translate them into percentages when applied into the regressions.
[41] BBB, BB, B rating levels are classified as "Average" in the Huazheng ESG rating system, where "Good" and "Poor" contain AAA, AA, A and CCC, CC, C, respectively.

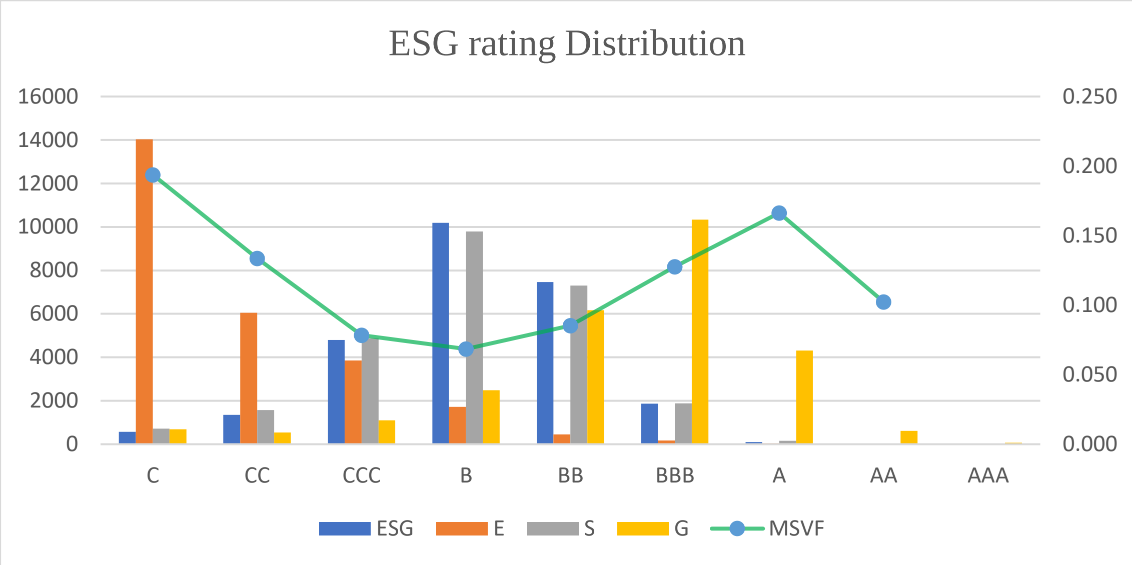
Table 4.1. Summary statistics of variables

	Firm-year obs.	Mean	Median	Std. Dev.	Percentile25	Percentile75	Min.	Max.
Dependent variable:								
MSVF	37220	0	-0.01	0.7	-0.33	0.37	-3.15	1.73
Target variables (*100):								
ESG score	37220	72.9	73.32	5.57	69.75	76.73	55.55	84.26
E score	37220	59.99	59.69	7.61	54.24	65.05	45.2	80.03
S score	37220	73.55	73.76	10.28	66.98	80.46	43.87	100
G score	37220	79.13	80.9	7.67	76.36	83.91	49.53	92.44
ESG disclosure	12184	24.56	24.39	7.74	18.73	29.01	9.91	49.29
E disclosure	12184	5.34	1.09	8.44	0	8.34	0	41.8
S disclosure	12184	11.3	10.43	7.18	7.38	14.57	0	33.33
G disclosure	12184	57.93	59.87	14.43	44.94	70.68	29.65	83.59
Information asymmetry:								
Earnings FE	16446	0.11	0.08	0.16	0.03	0.15	-0.36	0.77
Earnings SD	14113	0.43	0.05	1.53	0.02	0.11	0	7
illiquidity	56471	0	0	0.02	0	0	0	0.12
Bid_ask	43991	0.04	0.04	0.01	0.03	0.05	0.02	0.07
Control variables:								
Lev	39798	0.45	0.45	0.22	0.28	0.61	0.05	0.93
Profitability	39798	0.02	0.02	0.03	0.01	0.04	-0.05	0.13
CapEx	39798	20.2	20.1	1.66	19.18	21.15	15.71	24.75
Market-to-Book	39798	3.62	2.63	3.45	1.61	4.34	0.06	22.69
Analyst Coverage	39798	1.14	0.69	1.2	0	2.08	0	3.97

Volatility	39798	0.03	0.03	0.01	0.02	0.04	0.01	0.07

Notes: This table shows the summary statistics of our dependent variable, target variables, information asymmetry variables, and control variables. The dependent variable is the stock misvaluation measure (MSVF) of Rhodes-Kropf et al. (2015), considering SOEs' and Non-SOEs' classification in the benchmark regression. The target variables include the ESG score, environmental score (E score), social score (S score), governance score (G score), ESG disclosure score, environmental disclosure score (E disclosure), social disclosure score (S disclosure) and governance disclosure score (G disclosure). The information asymmetry variables include the earnings forecast error (Earnings FE), earnings forecast standard deviation (Earnings SD), illiquidity (illiquidity) and the bid-ask spread (Bid_ask). The control variables include the leverage ratio (Lev), profitability (Profitability), capital expenditure (CapEx), market-to-book ratio (Market-to-Book), analyst coverage (Analyst Coverage), and the volatility of stock returns (Volatility). For a detailed definition of these variables, refer to Section 4.3.2.

Figure 4.1. ESG rating distribution



Notes: this Figure shows the distribution of the ESG rating and its sub-ratings; (E, S, G) of A-shares listed in the Shanghai and Shenzhen stock markets of our data sample, as well as the mean value of stock misvaluation across 9 ESG ratings classifications. The ESG rating is provided by Sino-Securities Index information Services (Shanghai) Co. Ltd. as partner data of the Wind database. To avoid a misleading derived from data bias, the mean values of MSVF for the AAA rating of ESG are shown out, because there are no firms with this rating.

Table 4.2 shows the statistics of the ESG score and ESG disclosure score, both of which are sorted by industry and year. As shown in Panel A, the energy industry (Industry 4) has the lowest mean and median ESG scores across all industries. In contrast, financial industry (Industry 5) has the highest ESG score for both mean and median values, which are 76.58 and 77.73, respectively. These figures reflect the fact that firms' ESG scores vary greatly across different industries. Firms' ESG performance in high-tech and low waste emissions industries is better than their ESG performance in high energy-consuming and intensive carbon emission industries. Similarly, financial companies have higher ESG disclosure scores, as shown in Panel C. Financial firms which have less real property and physical products may tend to provide more information for investors to properly value their stocks. Panel B shows the ESG performance of firms across years. We do not find an improved ESG performance but observe an increasing number of firms with ESG scores. This observation is consistent with the finding in Panel D, where the mean value of the ESG disclosure score increases across years and also increases in the number of firms which choose to publicly disclose ESG information. This finding reflects the fact that more and more Chinese firms begin to disclose ESG contents, indicating that investors could access more of firm's characteristic information with this improved information transparency.

Figure 4.2 shows the year and industry condition of ESG rating. In Panel A, we find that, although the "Average" ESG rating level is the predominant rating during the sample periods, both "Good" and "Poor" ESG ratings are prevalent across the years. In contrast to an increase of the average ESG score, the mean value of stock misvaluation experienced a fluctuating decline across years. Similarly, the "Average" ESG rating level dominates the ESG rates across the industries in Panel B. Moreover, firms with "Good" ESG rates account for a higher percentage in the financial industry (Industry 5) than in other industries. In addition, both the ESG score and MSVF vary across sectors. The mean value of the ESG rates shows slight divergence across industries, ranging from 71.89 to 74.56. Meanwhile, the mean value of MSVF is positive across industries, with the exception of Industry 1, where Communications firms tend to be slightly undervalued.

Table 4.2. Descriptions of the ESG score and ESG disclosure score per industry and year.

Panel A	Per Industry					
Ind.	Firm-year obs.	Mean	Median	Max.	Mini.	Std. Dev.
1	828	72.86	73.2	85.93	54.07	5.76
2	3337	72.78	73.13	82.98	59.69	4.74
3	1354	72.39	72.62	82.32	56.94	4.77
4	645	71.85	72.53	81.14	54.61	5.4
5	560	76.58	77.73	86.24	60.06	5.73
6	996	75.69	76.36	84.57	62.08	4.55
7	1934	72.21	72.57	82.18	57.38	4.79
8	5115	72.57	72.82	82.52	58.77	4.72
9	4059	72.49	72.96	83.16	55.53	5.24
10	2836	72.91	73.13	83.17	59.87	4.6
11	827	72.86	73.11	82.25	56.7	4.83

Panel B	Per year					
Yr.	Firm-year obs.	Mean	Median	Max.	Mini.	Std. Dev.
2009	1876	72.3	72.56	81.86	57.69	4.52
2010	2176	73.15	73.35	82.67	58.77	4.76
2011	2364	73.41	73.82	83.14	57.76	4.9
2012	2366	73.12	73.41	83.71	57.59	4.95
2013	2458	72.76	73.04	83.52	57.59	4.99
2014	2679	72.46	72.73	83.1	58.13	4.96
2015	2855	72.2	72.75	82.86	55.8	5.38
2016	3309	72.87	73.22	84.14	56.23	5.48
2017	3464	73.36	73.75	84.92	56.22	5.72
2018	3621	72.82	73.53	85.37	52.78	6.67
2019	4002	73	73.78	85.47	52.54	6.65
2020	4485	73.1	73.83	84.6	54.41	6.06

ESG disclosure score descriptions per industry and per year

Panel C	Per Industry					
Ind.	Firm-year obs.	Mean	Median	Max.	Mini.	Std. Dev.
1	395	23.61	24.78	44.33	9.91	6.29
2	1507	23.61	23.55	40.58	10.74	6.6
3	854	23.96	23.67	46.26	10.83	7.11
4	247	25.34	24.46	57.09	9.91	10.46
5	601	29.73	28.88	55.47	12.55	9.77
6	679	23.4	23.26	39.76	10.83	6.35
7	1030	25.68	24.75	49.66	10.95	8.09
8	2501	24.19	23.9	47.14	9.91	7.57

Panel D	Per year					
Yr.	Firm-year obs.	Mean	Median	Max.	Mini.	Std. Dev.
2006	89	18.72	19.01	27.76	12.65	1.98
2007	104	18.65	19.01	23.4	12.44	2.07
2008	534	15.35	15.14	31.27	9.91	3.42
2009	595	17.24	17.32	34.72	9.91	4.18
2010	630	18.61	18.41	38.44	9.91	4.64
2011	706	19.3	19.06	41.72	9.91	4.75
2012	757	20.49	20.25	45.01	9.91	4.8
2013	801	20.95	20.05	48.09	9.91	4.91

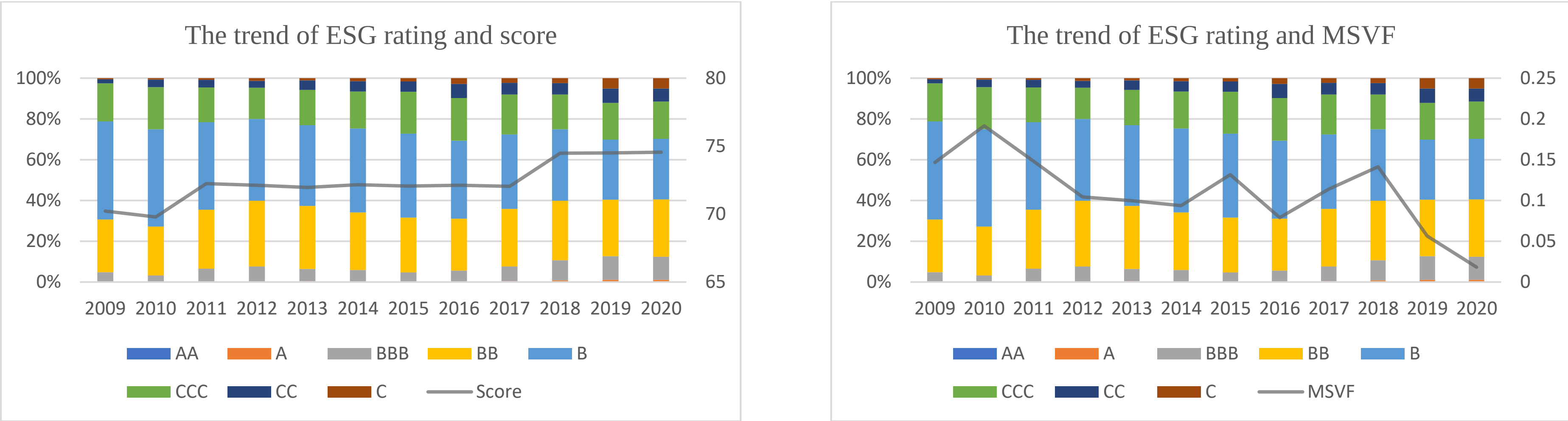
9	2532	24.23	23.37	49.69	9.91	7.99
10	1222	25.04	25.4	51.73	10.7	7.62
11	616	24.34	24.7	42.99	9.91	7.44

2014	867	20.88	19.83	49.36	9.92	5.45
2015	912	21.15	19.85	54.88	9.91	5.9
2016	1107	27.42	26.94	55.47	9.91	5.68
2017	1159	28.07	27.38	57.09	9.91	5.94
2018	1255	29.15	28.2	57.09	9.91	6.35
2019	1284	30.59	29.57	55.47	9.91	6.87
2020	1384	31.38	30.15	57.09	9.91	7.29

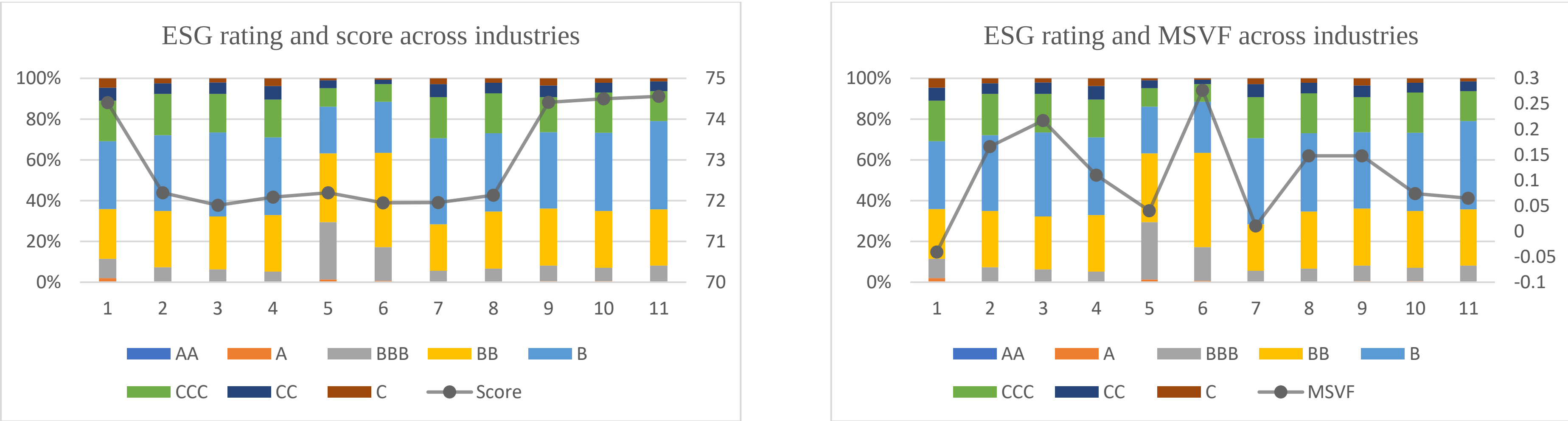
Notes: Panel A and Panel B show the summary statistics of the ESG score per industry and per year, respectively. Panel C and Panel D show the summary statistics of the ESG disclosure score per industry and per year, respectively. For reporting conciseness, we replace industry names with number. Industries 1 – 10 are Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Real Estate, Healthcare, Industrials, Materials, Technology and Utilities, respectively.

Figure 4.2. The ESG score across years and industries

Panel A

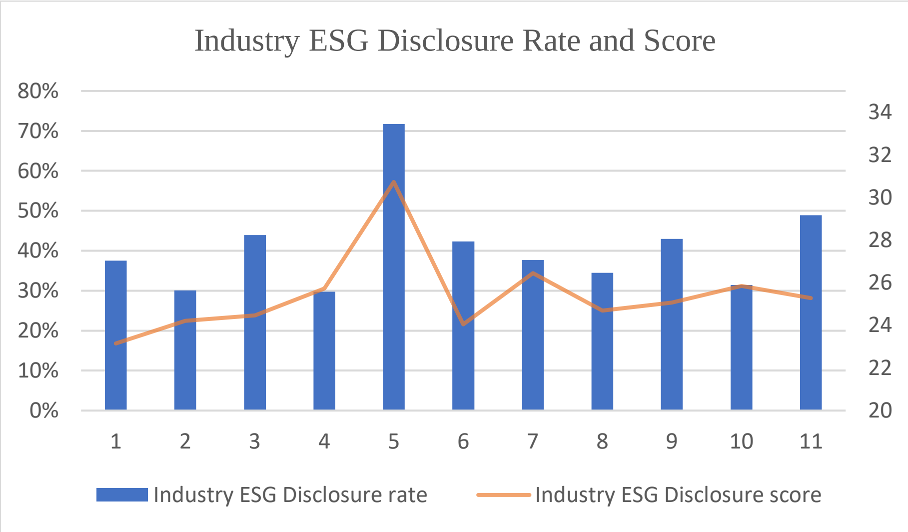


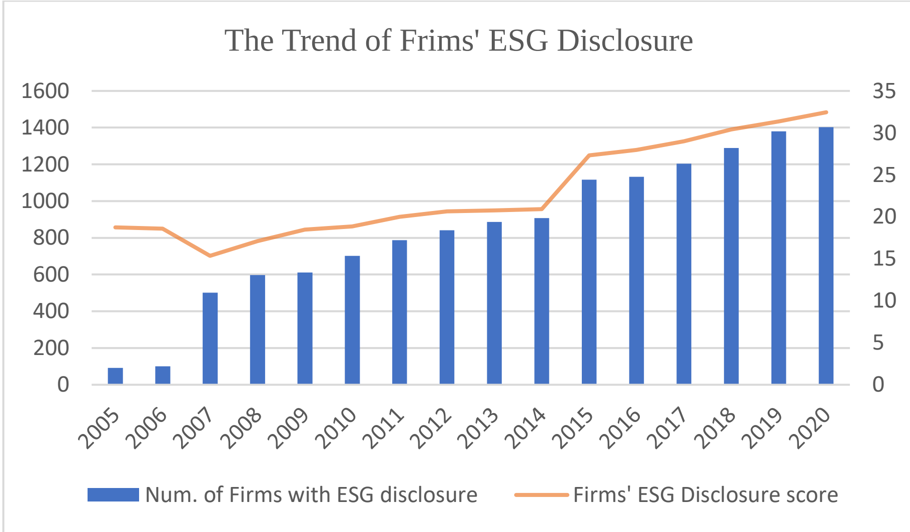
Panel B



Notes: Figure 4.2 shows the ESG rating conditions across years and industry. Panel A shows the trend of ESG rating, the mean value of ESG scores and mean value of stock misvaluation for A shares listed in Shanghai and Shenzhen stock markets across periods from 2009 to 2020. AAA, AA, A belongs to the good classification, BBB, BB, B belong to the average classification and CCC, CC, C belongs to the poor classification. Panel B shows each industry's ESG rating conditions, and the mean value of the ESG score, as well as the mean value of the ESG score across industries. Each industry contains firms listed in our data sample, covering 2009 to 2020. Industries 1 – 10 are Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Real Estate, Healthcare, Industrials, Materials, Technology and Utilities, respectively.

Figure 4.3. The ESG disclosure score across industries and years





Notes: This Figure shows the mean value of the ESG disclosure rate in each industry, as well as the mean value of the ESG disclosure score across industries and periods from 2005 to 2020 for A shares listed in the Shanghai and Shenzhen stock markets. Each industry contains firms listed in our data sample covering the years from 2005 to 2020.

We also report the ESG disclosure score by year and industry in Figure 4.3. Generally, the number of firms publicly disclosing ESG information increases steadily from 2006[42] to 2020, with a rapid growth in the number of disclosing firms in 2017. Although there are more than 1,400 firms that disclose ESG-related information in public reports, over half of listed Chinese firms still refrain from such disclosure. The average ESG disclosure score of firms also steadily increases over this period, indicating a growing tendency of firms to disclose ESG-related information in their financial statements and public reports. Moreover, the average ESG disclosure rate in most industries is lower than 50%, except for the financial industry where most firms publicly disclose ESG related information.

Verrecchia (1983) and Dye (1985) advocate that firms' ESG engagement can serve as a predictor of their ESG reporting practices. Under the voluntary ESG disclosure policy, firms with strong ESG performance tend to choose to report extensively, while firms with weak ESG performance are more likely to report minimally. Hence, we observe the ESG disclosure score performance under the ESG score classifications in Table 4.3. In this table, stocks are sorted into quintiles based on the ESG score within each industry at the end of each year. ESG5 (E5, S5, G5) contains stocks with the highest ESG (E,S,G) score. In contrast, ESG1 (E1, S1, G1) contains stocks with the lowest ESG (E,S,G) score. Table 4.3 reveals an increasing ESG (E,S,G) disclosure score across ESG (E,S,G) 1-5 quintiles. The difference between the top and bottom ESG (E,S,G) quintiles reveals a significantly positive value, indicating that firms with good ESG performance tend to report extensively and vice versa. This finding aligns with the literature. (Verrecchia,1983; Dye,1985; Cahan et al., 2015)

[42] This figure describes the raw data of the ESG disclosure score, covering a slightly longer than the period of our data sample which starts from 2009, as this could facilitate us to better observe the data trend without impacting on our research target.

Table 4.3 ESG disclosure score and ESG score

	ESG1	ESG2	ESG3	ESG4	ESG5	ESG5 - ESG1
ESG disclosure score	0.248	0.253	0.258	0.264	0.279	0.031***
						[11.53]
	E1	E2	E3	E4	E5	E5 - E1
E disclosure score	0.039	0.056	0.059	0.073	0.091	0.052***
						[16.68]
	S1	S2	S3	S4	S5	S5 - S1
S disclosure score	0.109	0.124	0.126	0.133	0.144	0.034***
						[14.42]
	G1	G2	G3	G4	G5	G5 - G1
G disclosure score	0.593	0.601	0.602	0.601	0.611	0.018***
						[3.50]

Notes: This table presents the average ESG (E,S,G) disclosure score in each ESG (E,S,G) quintiles. Stocks are sorted into quintiles based on the ESG score within each industry at the end of each year. ESG5 (E5, S5, G5) contains stocks with the highest ESG (E,S,G) score. ESG1 (E1, S1, G1) contains stocks with the lowest ESG (E,S,G) score. The number in parentheses is t-value. ***, **, * denote 1%, 5%, 10% significance levels.

4.4.2. Stock Misvaluation and ESG

In this section, we investigate the direct effect of ESG (E, S, G) scores on stock misvaluation. Model 1 of Table 4.4 reveals a negative relationship between the ESG score and stock misvaluation. A unit standard deviation (0.050) increase of the ESG score leads to a decrease in misvaluation of 0.80% (=0.050 * -0.16). In other words, an improvement of the ESG score decreases the difference between the actual market value and intrinsic firm value. The economic significance is that one unit increase in the ESG score leads to a ￥8 million lower market value, assuming that the intrinsic value remains constant at ￥1 billion. This finding is in contrast to that of Bofinger et al. (2022), who find a positive effect of ESG on stock misvaluation. There are three possible reasons for this difference. First, the Chinese government encourages companies to disclose ESG information to investors who can utilise this non-financial information to more properly value stocks and, hence, decrease stock misvaluation. Secondly, Chinese investors are dominated by individuals who are less educated and lack professional knowledge. Many investors may lack consciousness of ESG investment and are more likely to achieve a return associated with the good financial performance of a firm, rather than a potential long-term return brought about by ESG investment. Hence, the characteristics of Chinese investors decrease the possibility that investors with ESG preferences lead to stock overvaluation, which contributes to a opposite finding to that from the US market (Bofinger et al., 2022). Thirdly, a relatively low ESG quality coupled with associated costs may not be attractive enough for Chinese investors. The disclosure of Chinese ESG reports is policy-driven, with less disclosure content in detailed measures and follow-up feedback. Developing the ESG programme in China may be at the cost of firm value and harm shareholders' profit, as China has a comparatively short ESG development history and does not impose un-unified standards to regulate firms. Investors who perceive a high economic burden on firms stemming from ESG factors of relatively low quality are less likely to invest in ESG.

Table 4.4. Fixed effect regression results

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.305*** [8.19]	1.221*** [8.35]	1.183*** [8.09]	1.342*** [8.3]
Dep_{-1}	0.327*** [28.2]	0.327*** [28.22]	0.327*** [28.29]	0.327*** [28.19]
ESG Score_{-1}	-0.16* [-1.88]			
E Score_{-1}		-0.086 [-1.32]		
S Score_{-1}			0.016 [0.37]	
G Score_{-1}				-0.14** [-2.25]
Lev	0.251*** [5.62]	0.252*** [5.63]	0.253*** [5.66]	0.249*** [5.58]
Profitability	-1.869*** [-10.09]	-1.864*** [-10.07]	-1.86*** [-10.04]	-1.869*** [-10.1]
CapEx	-0.075*** [-9.94]	-0.075*** [-9.88]	-0.076*** [-10.02]	-0.076*** [-10.1]
Market-to-Book	0.003 [1.06]	0.003 [1.06]	0.003 [1.06]	0.003 [1.07]

Volatility	0.301	0.307	0.297	0.309
	[0.85]	[0.85]	[0.83]	[0.87]
Analyst Coverage	0.031***	0.03***	0.03***	0.031***
	[7.32]	[7.19]	[7.23]	[7.42]
Firm-year obs.	18401	18401	18401	18401
R-square	63.17%	63.17%	63.17%	63.18%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

We also find a negative effect of the G score on stock misvaluation in model 4. A one-unit standard deviation increase (0.065) of the G score causes the misvaluation to decrease by 0.91% (=0.065 * -0.14). However, both insignificant coefficients on the E and S scores reveal that there is no significant relationship between either the E score or S score on stock misvaluation in models 2 and 3. Our finding may be interpreted as follows. The G score measures the performance of firms' board and internal management, including leadership diversity, executive pay and shareholders interactions, among other aspects. Better corporate governance structures lead to higher information efficiency of the stock price and information disclosure (Lee et al., 2016). Hence, the negative effect of the G score on stock misvaluation is consistent with the literature. Compared with E and S, G is more important for investors to evaluate firms' managerial and controlling ability. In particular, Chinese firms have relatively poor environmental performance, to which Chinese investors may pay less attention. Hence, we don't observe significant effects of the E and S scores in Table 4.4. Our findings suggest that E, S and G should be viewed independently, as each dimension measures different aspects of a firm's performance, which have different implications for investors. Overall, the results in Table 4.4[43] show that the ESG performance taken together negatively affect the stock

[43] We use the percentage form of the ESG score in our regressions. In addition, we also take the logarithm of the ESG score to test the effect on valuation. Our results remain consistent. For conciseness, we do not report these results.

misvaluation orbit with less statistical significance, while the G score has a significant negative impact on stock misvaluation. In particular, the ESG score and the G score have negative impacts on stock misvaluation. We also consider the $\mathrm{MS}_{-1}^{\mathrm{DM}}$ as an additional control variable in regression models 1-4, as we find that $\mathrm{MS}_{-1}^{\mathrm{DM}}$ positively affects stock misvaluation in Chapter three. The results are robust and reported in Appendix B.1. Additionally, we test the impact of changes in ESG (E,S,G) score on misvaluation changes to capture the dynamic relationship. This setting allows to capture the effect of the improved/deteriorated ESG performance of firms on stock misvaluation changes. The results are robust and reported in Appendix B.2.

Although we find negative effects of ESG and G on misvaluation, this result does not indicate whether the ESG (E, S, G) score causes overvaluation or undervaluation. The reason for this is that the stock misvaluation measure is computed as the difference between the actual and intrinsic firm values. A decrease of the misvaluation measure caused by the ESG (G) score could be interpreted as the result of either a decrease of the overvaluation or an amplified undervaluation.

To further examine whether the ESG (E, S, G) score leads to the decreased overvaluation or increased undervaluation, we separate our data sample into two groups. Each contains either overvalued stocks or undervalued stocks. The overvalued group contains the top 30% overvalued stocks. In contrast, the undervalued groups comprise the bottom 30% undervalued stocks according to their respective stock misvaluation measures.

Panels A and B of Table 4.5 show the results regarding the effect of the ESG (E, S, G) score on overvaluation and undervaluation, respectively. In Table 4.5, we do not find any significant effect of the ESG score on stock misvaluation (MSVF) for both overvalued and undervalued groups, implying that the ESG score is not likely to cause the extreme overvaluation or undervaluation. This insignificant finding on ESG score on overvaluation and undervaluation may imply different valuation influences of each pillar.

Different from the insignificant sign of the S score on the misvaluation measure in Table 4.4, we find a positive sign of the S score on stock overvaluation in model 3 of Table 4.5, implying that the S score amplifies the existing overvaluation. The S score captures aspects such as labour issues, human rights and workplace safety, driving firms' reputation and performance (Bissoondoyal-Bheenick et al., 2023). A higher S score leads to a higher stock overvaluation, suggesting that market participants focus more on a firm's social performance, ultimately leading to an enhanced valuation. Moreover, models 4 and 8 show that the relationships between the G score and over- or under-valuation are both significant, though the signs are opposite, with the coefficients being -0.311 (t= -2.6) for the overvaluation sample and 0.184 (t=2.53) for the undervaluation sample. Referring to the negative sign of the G score in Table 4.4, this result indicates that the G score affects stock misvaluation through simultaneously reducing the overvaluation and undervaluation. In other words, the G score corrects the stock misvaluation towards the intrinsic value in both directions. This finding tells a more accurate story than that of Table 4.4 of the valuation effect of the G score, specifically better corporate governance would move the stock value towards its true value.

Table 4.5. Stock misvaluation (most over- and undervalued 30% firms) regressed on the ESG score, E score, S score, G score

Panel A: Most overvalued firms - Top 30%					Panel B: Most undervalued firms - bottom 30%			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF
Intercept	1.291***	1.231***	1.14***	1.509***	-0.02	0.05	0.043	-0.127
	[5.46]	[5.73]	[5.35]	[6.4]	[-0.12]	[0.33]	[0.29]	[-0.79]
Dep_{-1}	0.141***	0.141***	0.141***	0.139***	0.113***	0.112***	0.112***	0.113***
	[7.73]	[7.77]	[7.8]	[7.64]	[8.75]	[8.66]	[8.66]	[8.76]
ESG Score_{-1}	-0.095				0.091			
	[-0.59]				[0.91]			
E Score_{-1}		0.001				-0.053		
		[0.01]				[-0.74]		
S Score_{-1}			0.212***				-0.043	
			[2.58]				[-1]	
G Score_{-1}				-0.311***				0.184**
				[-2.6]				[2.53]
Lev	0.21***	0.212***	0.211***	0.204***	0.049	0.046	0.047	0.052
	[3.12]	[3.14]	[3.15]	[3.05]	[1.19]	[1.11]	[1.14]	[1.26]
Profitability	-0.941***	-0.932***	-0.895***	-0.948***	-0.992***	-0.993***	-0.995***	-0.98***
	[-3.35]	[-3.32]	[-3.18]	[-3.38]	[-4.72]	[-4.72]	[-4.74]	[-4.67]
CapEx	-0.038***	-0.039***	-0.042***	-0.04***	-0.036***	-0.035***	-0.035***	-0.034***
	[-3.59]	[-3.61]	[-3.92]	[-3.78]	[-4.97]	[-4.85]	[-4.83]	[-4.76]
Market-to-Book	0.002	0.002	0.002	0.002	0.011***	0.011***	0.011***	0.011***
	[1.62]	[1.62]	[1.63]	[1.61]	[2.74]	[2.78]	[2.77]	[2.62]
Volatility	-0.563	-0.567	-0.535	-0.526	0.406	0.403	0.403	0.402
	[-0.65]	[-0.66]	[-0.62]	[-0.62]	[1.28]	[1.27]	[1.28]	[1.26]
Analyst Coverage	0.002	0.002	0.001	0.003	0.028***	0.028***	0.028***	0.027***
	[0.22]	[0.2]	[0.16]	[0.33]	[6.27]	[6.27]	[6.3]	[6.03]
Firm-year obs.	4534	4534	4534	4534	4139	4139	4139	4139

R-square	52.22%	52.22%	52.31%	52.32%	46.73%	46.73%	46.73%	46.84%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores for over- and undervalued stocks. Models 1 to 4 of Panel A represent the analyses for overvalued stocks, which are the top 30% of stocks according to the stock misvaluation measure. Models 5 to 8 of Panel B represent the analyses for undervalued stocks, which are the bottom 30% of stocks according to the stock misvaluation measure. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

To address the concern that our result is sensitive to the definition of overvaluation and undervaluation, we also check the Table 4.5 results through using the median value of stock misvaluation and the zero value of stock misvaluation to determine the demarcation of stock overvaluation and undervaluation, respectively. Our findings remain unchanged during these tests and the results are reported in Appendices B.3 and B.4, respectively.

The measure perceived does not help answer the question of by how much a chosen explanatory variable affects the absolute size of the misvaluation (whether over- or undervaluation). To examine this question without explanatory differentiating between overvaluation and undervaluation, we introduce the absolute value of the MSVF as the dependent variable in Table 4.6.

Table 4.6. Absolute value of stock misvaluation regressed on the ESG score, E score, S score, G score

	(1) |MSVF|	(2) |MSVF|	(3) |MSVF|	(4) |MSVF|
Intercept	0.474*** [3.79]	0.397*** [3.53]	0.359*** [3.21]	0.645*** [5.14]
$\|Dep_{-1}\|$	0.215*** [17.55]	0.215*** [17.56]	0.215*** [17.56]	0.213*** [17.51]
ESG Score_{-1}	-0.089 [-1.25]			
E Score_{-1}		0.037 [0.68]		
S Score_{-1}			0.114*** [3.21]	
G Score_{-1}				-0.217*** [-4.28]
Lev	0.088** [2.54]	0.089*** [2.59]	0.087** [2.53]	0.082** [2.39]
Profitability	-0.138 [-0.89]	-0.131 [-0.85]	-0.123 [-0.79]	-0.146 [-0.95]
CapEx	-0.009 [-1.51]	-0.009 [-1.62]	-0.011* [-1.91]	-0.01* [-1.8]
Market-to-Book	0.002 [1.46]	0.002 [1.46]	0.002 [1.45]	0.002 [1.49]
Volatility	-0.322 [-0.74]	-0.329 [-0.75]	-0.309 [-0.7]	-0.305 [-0.7]

Analyst Coverage	-0.006*	-0.006*	-0.006*	-0.005
	[-1.72]	[-1.75]	[-1.71]	[-1.38]
Firm-year obs.	18401	18401	18401	18401
R-square	46.52%	46.52%	46.55%	46.59%

Notes: This table shows the fixed effect regression results of the absolute value of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

We find that the S score is positively associated with the absolute value of stock misvaluation, indicating the S score leads to a more serious stock misvaluation. When the standard deviation (0.10) of the S score increases by one unit, the absolute value of stock misvaluation will raise by 1.14%. In contrast, the G score has a negative impact on the absolute value of stock misvaluation. The negative effect of the G score indicates that the G score has a correcting function for stock misvaluation, by driving either the overvaluation or the undervaluation of a company towards its intrinsic value. These findings of both the S score and G score effects are consistent with the results presented in Table 4.5.

Unlike the ESG score, which measures a company's ESG performance, the ESG rating delivers investors information about the level of ESG involvement by a company. The ESG rating may be more effective at capturing investors' attention than a purely abstract figure – the ESG score. For instance, a 70 score is a ESG rating threshold between BBB and BB for a company. When a company's rating is 69, a one-point improvement can result in a better ESG rating. This small gap might seem inconsequential in economic terms. However, it can significantly impact investors' perceptions of this company when the ESG performance is reported in a rating format. Another point of the ESG rate that attracts investors is that the ESG rate is more intuitive, making it easier for investors to compare companies' ESG performance. Therefore, we introduce the concept of ESG rating shocks to capture the changes in ESG ratings. A ESG shock is defined as 1 when a firm's ESG rating changes from a comparatively low level to a high level, otherwise it is identified as 0 when the rating drops from a high level to a low level.

Table 4.7 shows the result of the effect of ESG rating shocks on stock misvaluation. We find that S shocks have a positive impact on stock misvaluation in model 3. The effect of the S rating shocks suggests that firms' better performance in social responsibility increases the existing stock misvaluation. This finding is consistent with our previous results, indicating that the change of S rating is one of the factors affecting Chinese investors in making their investment decisions. However, we do not find ESG, E and G rating changes having any effects on stock misvaluation. The decreasing significance of ESG (E, S, G) scores could potentially be attributed to the lower volatility of ESG rate data, which in turn results in a larger standard deviation and smaller t-values.

Table 4.7. Stock misvaluation regressed on ESG, E, S, G rating shocks

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.154***	1.16***	1.158***	1.169***
	[8.63]	[8.69]	[8.67]	[8.72]
Dep_{-1}	0.32***	0.32***	0.32***	0.32***
	[25.43]	[25.42]	[25.43]	[25.39]
ESG shock	0.009			
	[1.44]			
E shock		0		
		[0.03]		
S shock			0.01*	
			[1.89]	
G shock				-0.008
				[-1.38]
Lev	0.267***	0.266***	0.265***	0.264***
	[6.19]	[6.17]	[6.16]	[6.14]
Profitability	-1.202***	-1.199***	-1.201***	-1.196***
	[-3.1]	[-3.1]	[-3.1]	[-3.09]
CapEx	-0.074***	-0.074***	-0.074***	-0.074***
	[-10.71]	[-10.72]	[-10.75]	[-10.72]
Market-to-Book	0.002***	0.002***	0.002***	0.002***
	[5.15]	[5.16]	[5.15]	[5.17]
Volatility	0.255	0.252	0.255	0.248

	[0.92]	[0.91]	[0.92]	[0.89]
Analyst Coverage	0.028***	0.028***	0.028***	0.028***
	[6.18]	[6.18]	[6.2]	[6.22]
Firm-year obs.	18401	18401	18401	18401
R-square	62.88%	62.87%	62.88%	62.88%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the ESG (E, S, G) rating shocks in models 1, 2, 3, and 4 respectively. A rating shock is defined as 1 when a company's rating upgrades from a low level to a high level, while it is defined as 0 when a company's rating downgrades from a high level to a low level. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

4.4.3. Influencing role of Information Availability

As discussed in the literature review section, the effect of ESG score on stock misvaluation may be affected by information availability. In this section, we will introduce the following variables: the ESG (E, S, G) disclosure score and information asymmetry measures[44], including the earnings forecast error, earnings forecast standard deviation, illiquidity and the bid-ask spread. In order to examine the influencing role of information availability in the relationship between ESG score and misvaluation, we include an interaction term between the target variables and the ESG scores in the regression. This interaction variable captures the effect of ESG on misvaluation that is attributed to the impact of information availability.

Table 4.8 reports the influencing role of the ESG (E,S,G) disclosure score on the relationship between ESG and misvaluation. There are two main findings in Table 4.8. First, the negative baseline finding of ESG (G) score on misvaluation measure in Table 4.4 remains in Table 4.8. Second, Table 4.8 reveals a positive and significant coefficient on the interaction

[44] We also employ four information asymmetry measures from Bofinger et al. (2022) and find that none of them has a significant effect. This finding is consistent with Bofinger et al. (2022), who find an insignificant effect of information asymmetry on the ESG-misvaluation relationship in the US market. The results are reported in Appendix B.5.

variable between the ESG (G) score and ESG (G) disclosure score, suggesting that the ESG (G) disclosure score could positively influence the ESG - misvaluation relationship.

Taking ESG score as an example, the composite coefficient of ESG score is (-0.752+2.561*ESG disclosure score), which implies that the impact of ESG score on misvaluation is contingent upon the ESG disclosure score. Taking the mean value of ESG disclosure score into the function, we find the coefficient of ESG score becomes -0.086, which is higher than the isolated ESG coefficient (-0.752), suggesting that the impact of ESG score on misvaluation enhances. Figure 4.4 presents the dynamic coefficient of ESG (G) score, conditioned on ESG disclosures.

However, this impact on overvaluation and undervaluation is diverse, indicating two different directions. One is that, given ESG score, a rise in ESG disclosure score (more transparent) would lead to the impact of the given ESG score on overvaluation (when MSVF > 0) to rise, causing overvalued stocks to be more overvalued when compared to the impact of the original ESG score in isolation. This means that ESG disclosure score strengthens the influence of ESG score on overvaluation. The other is that, given ESG score, a rise in ESG disclosure score (more transparent) would cause the impact of the given ESG score on undervaluation (when MSVF < 0) to rise too, but making undervalued stocks less undervalued. This implies that the ESG disclosure score mitigates the influence of ESG score in undervaluation. The same analysis applies to the G score in a similar manner as it does to the ESG score.

The influencing role of the ESG disclosure score in the relationship between ESG score and misvaluation aligns with the Chinese situation. Chinese voluntary ESG disclosure policy creates the likelihood for firms to extensively report ESG practices to attract investors when their ESG performance is strong. Hence, investors tend to hold optimistic perspectives and value more on these firms with ESG performance. This view is consistent with our finding in

Table 4.3, therefore further affirming the advocate of Verrecchia (1983) and Dye (1985) that firms with strong ESG performance are more likely to choose to report extensively under a voluntary disclosure framework. As a result, for overvalued firms, the positive perception of investors derived from the increasing ESG disclosure leads to a greater extent of overvaluation. Likewise, for undervalued stocks, positive investors' belief stemming from the ESG disclosure serves to mitigate the undervaluation.

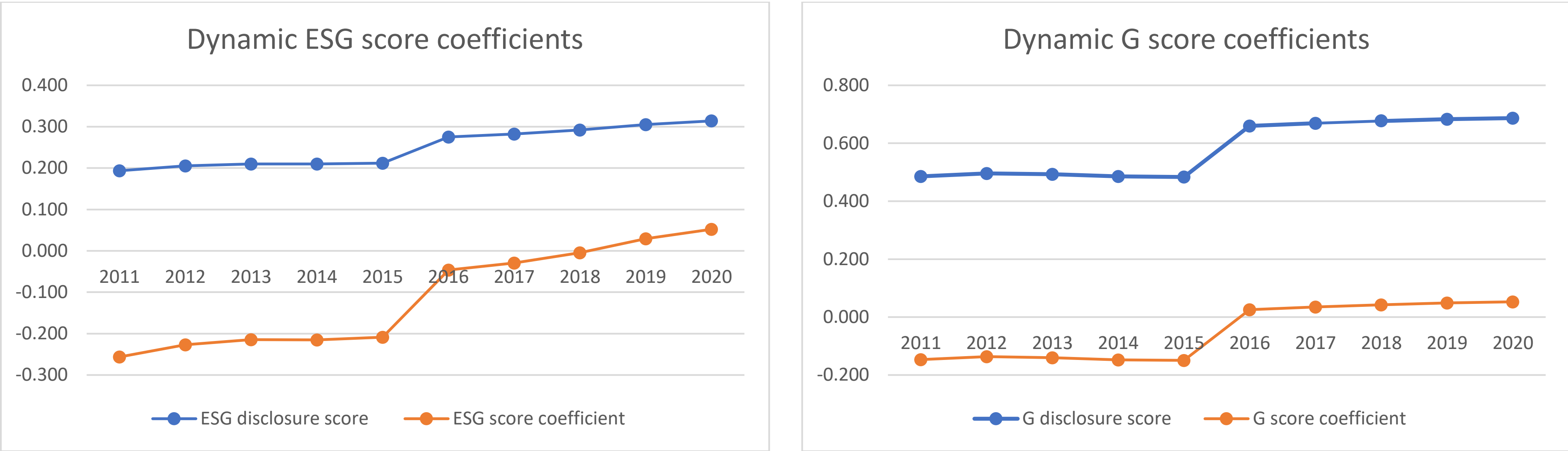
Table 4.8. Influencing role of the ESG disclosure score

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	3.331***	2.896***	2.722***	3.218***
	[9.66]	[11.76]	[10.66]	[9.45]
Dep_{-1}	0.351***	0.348***	0.351***	0.352***
	[19.9]	[19.85]	[19.95]	[19.96]
ESG score_{-1}	-0.752**			
	[-2.28]			
$\text{ESG disclosure score}_{-1}$	-1.709*			
	[-1.88]			
$\text{ESG score}_{-1} \times \text{ESG disclosure score}_{-1}$	2.561**			
	[2.13]			
E score_{-1}		-0.298***		
		[-2.87]		
$\text{E disclosure score}_{-1}$		-0.541		
		[-1.05]		
$\text{E score}_{-1} \times \text{E disclosure score}_{-1}$		1.229		
		[1.53]		
S score_{-1}			-0.059	
			[-0.55]	
$\text{S disclosure score}_{-1}$			-0.371	
			[-0.65]	
$\text{S score}_{-1} \times \text{S disclosure score}_{-1}$			0.571	
			[0.78]	
G score_{-1}				-0.63**
				[-2.12]
$\text{G disclosure score}_{-1}$				-0.735*
				[-1.95]
$\text{G score}_{-1} \times \text{G disclosure score}_{-1}$				0.994**
				[2.19]
Lev	0.295***	0.29***	0.284***	0.29***
	[4.46]	[4.41]	[4.32]	[4.41]
Profitability	-1.807***	-1.821***	-1.801***	-1.806***

	[-6.57]	[-6.64]	[-6.54]	[-6.54]
CapEx	-0.088***	-0.083***	-0.08***	-0.085***
	[-6.99]	[-7.02]	[-6.63]	[-6.88]
Market-to-Book	0.017***	0.017***	0.017***	0.017***
	[3.95]	[4.07]	[3.95]	[3.95]
Volatility	-1.326***	-1.262***	-1.372***	-1.398***
	[-2.98]	[-2.83]	[-3.08]	[-3.13]
Analyst Coverage	0.031***	0.029***	0.03***	0.031***
	[5.33]	[5.07]	[5.16]	[5.31]
Firm-year obs.	7460	7460	7460	7460
R-square	72.42%	72.44%	72.37%	72.40%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the ESG (E, S, G) disclosure score in models 1, 2, 3 and 4, respectively. The ESG disclosure score measures the extent of a company publicly disclosing its ESG information, rather than its ESG performance. To better report the effect of the ESG disclosure score, we transfer the ESG disclosure score from a scale of 100 to a percentile. We also include an interactive variable in each regression. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Figure 4.4 Dynamic coefficients of ESG (G) score



Notes: This figure plots the dynamic coefficient of ESG (G) score, conditioned on ESG disclosure score. We calculate the cross-sectional mean values of ESG and G disclosure scores each year, then taking the values into the ESG and G composite coefficient functions: (-0.752+2.561*ESG disclosure score) and (-0.63 + 0.994*G disclosure score) to calculate the coefficients of ESG and G scores each year.

4.4.4. Macroeconomic Environment

Previously, we find that the ESG score and G score have negative impacts on stock misvaluation and this effect is influenced by the ESG (G) disclosure score. The relationship between ESG and stock misvaluation may be affected by macroeconomic fluctuation (Vural-Yavaş, 2021). Firms may increase their ESG performance during high uncertainty periods. In this section, we investigate whether the effect of the ESG (E, S, G) score is affected by macroeconomic movement. In order to capture the effect of long-term macroeconomic movement, we include an EPU shock and relevant interaction terms between the shock and ESG scores. Table 4.9 reports the effect of our target variables. We find that coefficients on EPU shocks and the relevant interaction variables are not significant. Overall, we do not find evidence that the macroeconomic variables affect stock misvaluation and the ESG - misvaluation relationship. In addition, our main findings still hold in Table 4.9, where the ESG score and G score negatively and significantly affect the stock misvaluation measure.

Table 4.9. EPU shock effect

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.295***	1.192***	1.169***	1.315***
	[8.5]	[8.71]	[8.58]	[8.54]
Dep_{-1}	0.319***	0.32***	0.32***	0.319***
	[25.32]	[25.34]	[25.4]	[25.31]
EPU shock	-0.102	-0.02	-0.047	-0.058
	[-1.3]	[-0.47]	[-1.28]	[-0.79]
ESG score_{-1}	-0.189**			
	[-2]			
$\text{ESG score}_{-1} *$ EPU shock	0.138			
	[1.3]			
E score_{-1}		-0.084		
		[-1.2]		
$\text{E score}_{-1} *$ EPU shock		0.031		
		[0.45]		
S score_{-1}			-0.01	
			[-0.22]	
$\text{S score}_{-1} *$ EPU shock			0.063	

			[1.27]	
G score_{-1}				-0.15**
				[-2.15]
G score_{-1} * EPU shock				0.07
				[0.78]
Lev	0.263***	0.264***	0.265***	0.262***
	[6.1]	[6.14]	[6.16]	[6.07]
Profitability	-1.207***	-1.201***	-1.201***	-1.205***
	[-3.1]	[-3.1]	[-3.1]	[-3.1]
CapEx	-0.074***	-0.074***	-0.074***	-0.075***
	[-10.65]	[-10.63]	[-10.72]	[-10.8]
Market-to-Book	0.002***	0.002***	0.002***	0.002***
	[5.2]	[5.15]	[5.17]	[5.21]
Volatility	0.277	0.276	0.272	0.284
	[0.92]	[0.9]	[0.89]	[0.94]
Analyst coverage	0.028***	0.028***	0.028***	0.029***
	[6.25]	[6.16]	[6.18]	[6.33]
Firm-year obs.	18399	18399	18399	18399
R-square	62.88%	62.88%	62.88%	62.88%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the ESG (E, S, G) score as well as EPU shocks in models 1, 2, 3, and 4, respectively. An EPU shock is defined as 1 when EPU increases from a low figure to a high one from year t to year t+1, and defined as 0 when it decreases from year t to year t+1. The iterative item is the multiple of the ESG (E, S, G) score and the EPU shock. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

4.5. Robustness Check

4.5.1. Alternative ESG Score

Previous analyses have shown that the ESG score and G score could influence stock misvaluation. However, this relationship may be subject to the non-uniform standard of the ESG score. According to Dorfleitner et al. (2015), a firm's ESG score and rating varies among data providers. To reduce this concern, we employ the ESG score from the Wind database[45] to re-examine the ESG-misvaluation relationship. We find that the ESG score and all three pillars

[45] The Wind database is a popular and mature data provider for the Chinese stock market. The ESG score starts from 2015 and ranges from 1 to 10 to measure a company's ESG performance, with 1 being the lowest score indicating poor ESG practice, and10 representing the best.

negatively and significantly impact stock misvaluation in Table 4.10. This result indicates that the ESG (E, S, G) score could reduce stock misvaluation. In particular, the ESG score contains the largest magnitude of the negative coefficient compared with other scores, at -0.44 (t=-3.33). The findings of models 1 and 4 are consistent with the result of Table 4.4. The difference lies in that coefficients on the E score and S score also become negative and significant. This phenomenon may be caused by different standards of measuring the ESG (E, S, G) score and the length of the data sample. The Wind ESG data cover a comparatively shorter period, starting from 2015 when the number of firms with ESG disclosure started to increase. Overall, our main finding holds when using the ESG score from different database providers.

Table 4.10. The ESG score of the Wind database

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.781***	1.648***	1.579***	1.587***
	[4.25]	[3.89]	[3.71]	[3.75]
Dep_{-1}	-0.335***	-0.338***	-0.334***	-0.334***
	[-11.65]	[-11.86]	[-11.56]	[-11.51]
ESG $Score_{-1}$	-0.04***			
	[-3.33]			
E $Score_{-1}$		-0.01**		
		[-2.04]		
S $Score_{-1}$			-0.009***	
			[-3.29]	
G $Score_{-1}$				-0.007***
				[-3.65]
Lev	0.49***	0.467***	0.501***	0.514***
	[3.57]	[3.42]	[3.63]	[3.74]
Profitability	-2.455***	-2.394***	-2.487***	-2.523***
	[-5.96]	[-5.82]	[-6.07]	[-6.1]
CapEx	-0.109***	-0.113***	-0.109***	-0.108***
	[-4.96]	[-5.16]	[-4.94]	[-4.91]
Market-to-Book	0.006	0.006	0.006	0.007
	[0.81]	[0.86]	[0.84]	[0.85]
Volatility	2.244*	2.48*	2.042	1.755
	[1.75]	[1.95]	[1.58]	[1.34]
Analyst Coverage	-0.001	0	-0.002	-0.002
	[-0.09]	[-0.03]	[-0.14]	[-0.15]
Firm-year obs.	3038	3038	3038	3038

R-square	87.46%	87.43%	87.46%	87.47%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the Wind lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

4.5.2. Industry Bias

Table 4.2 reveals that the ESG score varies across industries. The mean and median ESG scores of financial firms are much higher than for other industries. The high ESG score of financial firms is mainly attributed to the minimal weight of environment in which financial institutions have a negligible impact on environment aspects, as financial firms which belong to high-tech and service provider sectors do not have heavy carbon emissions and waste disposal requirements. To address the concern that our result is driven by skewed environmental data for the financial industry, we delete financial firms from our data sample and re-run the benchmark regression. We find that the E score becomes negatively related with the stock misvaluation measure. Meanwhile, the coefficients of the ESG score and G score remain negative and significant. The result is reported in Table 4.11.

Table 4.11. Excluding firms in the financial industry

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.093*** [6.89]	1.026*** [7.12]	0.974*** [6.79]	1.152*** [7.16]
Dep_{-1}	0.316*** [28.51]	0.316*** [28.52]	0.317*** [28.59]	0.316*** [28.49]
ESG Score_{-1}	-0.148* [-1.68]			
E Score_{-1}		-0.119* [-1.83]		
S Score_{-1}			0.03 [0.66]	
G Score_{-1}				-0.151** [-2.29]
Lev	0.165*** [4.06]	0.165*** [4.05]	0.167*** [4.1]	0.163*** [4.01]

Profitability	-2.049***	-2.044***	-2.039***	-2.051***
	[-10.97]	[-10.95]	[-10.92]	[-10.99]
CapEx	-0.063***	-0.062***	-0.064***	-0.064***
	[-8.48]	[-8.39]	[-8.59]	[-8.68]
Market-to-Book	0.018***	0.018***	0.018***	0.018***
	[8.17]	[8.17]	[8.14]	[8.2]
Volatility	-0.94***	-0.94***	-0.95***	-0.926***
	[-3.19]	[-3.19]	[-3.22]	[-3.15]
Analyst Coverage	0.026***	0.025***	0.025***	0.026***
	[6.28]	[6.15]	[6.21]	[6.42]
Firm-year obs.	17503	17503	17503	17503
R-square	62.54%	62.54%	62.53%	62.54%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. We exclude financial firms in the regressions. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

To ensure that firms' ESG scores for different sectors are comparable, the ESG evaluation of data providers considers the influence of the industry a firm operates in. Investors also evaluate a firms' ESG performance relative to its peers (Ding et al., 2016). This behaviour would influence investors' decisions and ultimately transfer to the association between ESG and stock valuation, due to the industry bias. To further alleviate the concern of industry bias, we adjust the ESG (E, S, G) score by the industry mean. In particular, we adjust a company's ESG (E,S,G) score by deducting the mean value of the scores in respective industries (Ghoul et al., 2011). Table 4.12 shows the industry-adjusted ESG effect on misvaluation. We find our main finding does not change with respect to the negative sign and statistical significance of the coefficients on the ESG and G scores in models 1 and 4.

Table 4.12. Industry adjusted ESG score

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.177***	1.165***	1.179***	1.195***
	[8.15]	[8.05]	[8.15]	[8.24]
Dep_{-1}	0.337***	0.337***	0.337***	0.337***
	[29.01]	[29.05]	[29.07]	[28.99]
$\text{ESG score}^{\text{Ind}}{}_{-1}$	-0.149*			
	[-1.7]			

E $\text{score}^{\text{Ind}}_{-1}$		-0.08		
		[-1.2]		
S $\text{score}^{\text{Ind}}_{-1}$			0.009	
			[0.2]	
G $\text{score}^{\text{Ind}}_{-1}$				-0.127**
				[-1.96]
Lev	0.256***	0.257***	0.258***	0.254***
	[5.68]	[5.7]	[5.72]	[5.65]
Profitability	-1.816***	-1.813***	-1.812***	-1.816***
	[-9.76]	[-9.74]	[-9.73]	[-9.76]
CapEx	-0.074***	-0.074***	-0.075***	-0.075***
	[-9.83]	[-9.84]	[-9.9]	[-9.9]
Market-to-Book	0.003	0.003	0.003	0.003
	[1.03]	[1.03]	[1.03]	[1.04]
Volatility	0.318	0.323	0.324	0.323
	[0.89]	[0.9]	[0.9]	[0.9]
Analyst Coverage	0.03***	0.03***	0.03***	0.03***
	[7.18]	[7.07]	[7.09]	[7.2]
Firm-year obs.	17964	17964	17964	17964
R-square	61.88%	61.88%	61.88%	61.89%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. The ESG (E,S,G) score is adjusted by the industry mean to alleviate the industry bias. We calculate a company's ESG (E,S,G) score each year by reducing the industry mean on that year. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

4.5.3. Endogeneity

The significant relationship between the ESG score and stock misvaluation may be also challenged by endogeneity concerns, such as simultaneity and reverse causality. Although we have carefully added control variables that are relevant to stock misvaluation from the literature, and have included a lagged dependent variable into the regression, we need more robustness checks to further alleviate the potential endogeneity concern. We use two-stage least squares regression with the mean value of the ESG (E,S,G) score from each industry serving as the instrumental variable (Ghoul et al., 2011; Kim et al., 2014). We expect the industry mean to be uncorrelated with the firm specific error term and stock misvaluation, while being correlated with the firm-level ESG (E,S,G) score.

Panel A of Table 4.13 shows the results from the two-stage least squares analysis of the effect of the ESG score on stock misvaluation. We can see that the ESG score and G score are negatively and significantly correlated with stock misvaluation. This finding underlines the result of the benchmark regression. We also follow Arellano and Bover (1995) and use a dynamic panel GMM model to alleviate the endogeneity issue of fixed effect regression. The dynamic panel GMM model allows us to instrument all independent variables with past lags. Panel B of Table 4.13 reports the results from the dynamic GMM analysis of the ESG score on misvaluation. We find that the ESG (S,G) score shows a significantly negative effect on the misvaluation measure, which complements our prior findings. The P-value of the AR(3) test rejects the serial correlation.

Table 4.13. Endogeneity

Panel A Two-stage least square regression

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	0.199*** [4.05]	0.136*** [3.61]	0.13*** [3.26]	0.191*** [4.21]
Dep_{-1}	0.7*** [135.32]	0.7*** [135.37]	0.701*** [135.41]	0.7*** [135.39]
ESG Score_{-1}	-0.001** [-2.23]			
E Score_{-1}		0 [-0.99]		
S Score_{-1}			0 [-0.44]	
G Score_{-1}				-0.001** [-2.38]
Lev	-0.003 [-0.19]	-0.001 [-0.08]	-0.001 [-0.06]	-0.008 [-0.6]
Profitability	0.074 [0.84]	0.056 [0.64]	0.06 [0.68]	0.07 [0.79]
CapEx	-0.007*** [-3.67]	-0.007*** [-3.57]	-0.007*** [-3.83]	-0.007*** [-3.64]
Market-to-Book	0 [0.36]	0 [0.48]	0 [0.48]	0 [0.47]
Volatility	0.084 [0.88]	0.088 [0.92]	0.088 [0.92]	0.087 [0.91]

Analyst Coverage	0.024***	0.023***	0.023***	0.023***
	[9.35]	[9.14]	[9.06]	[9.34]
Firm-year obs.	24652	24652	24652	24652
Adj.R-square	46.73%	46.73%	46.72%	46.73%

Panel B Dynamic GMM regression

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	16.494*	6.594	7.514	21.307**
	[1.78]	[1.09]	[1.57]	[2.24]
Dep_{-2}	0.585**	0.235	0.329*	0.911***
	[2.17]	[1.61]	[1.89]	[2.81]
Dep_{-1}	0.734***	0.598***	0.503***	0.998***
	[4.11]	[5.26]	[3.19]	[4.95]
$\mathrm{ESG\ Score}_{-1}$	-0.123*			
	[-1.68]			
$\mathrm{E\ Score}_{-1}$		-0.051		
		[-1.12]		
$\mathrm{S\ Score}_{-1}$			-0.077**	
			[-2.17]	
$\mathrm{G\ Score}_{-1}$				-0.116**
				[-1.97]
Lev	-0.529	-0.119	-0.091	-1.372
	[-0.3]	[-0.11]	[-0.06]	[-1.01]
Profitability	-8.235	-10.648*	-6.922	7.553
	[-0.91]	[-1.86]	[-0.8]	[0.83]
CapEx	-0.368	-0.157	-0.099	-0.601**
	[-1.38]	[-0.86]	[-0.51]	[-2.24]
Market-to-Book	0.036	0.009	0.023	0.045**
	[1.27]	[0.6]	[1.16]	[1.96]
Volatility	-19.085*	-15.377*	-14.502	-16.652**
	[-1.73]	[-1.89]	[-1.61]	[-2.21]
Analyst Coverage	0.113	0.145	0.068	-0.234
	[0.71]	[1.48]	[0.46]	[-0.97]
Firm-year obs.	10339	10339	10339	10339
AR(2)p	.	0.206	.	.
AR(3)p	0.129	.	0.508	0.306
Durbin-Watson	1.999	2.000	2.000	2.000
Adj.R-square	38.79%	25.63%	29.04%	46.16%

Notes: This table shows the two-stage least squares and dynamic panel GMM regressions where stock misvaluation (MSVF) is regressed on the lagged ESG score and E, S, G scores, respectively. The lagged ESG score is instrumental with the mean value of each industry in Panel A. The dynamic panel GMM of Panel B allows us to instrument all of the independent variables. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

To summarise, the two-stage least squares and dynamic panel GMM regressions help us imitate the endogeneity issue. Overall, the findings of these two models do not contradict our prior findings. Hence, we conclude that the ESG (G) score could significantly and negative impact stock misvaluation.

4.6. Conclusion

In conclusion, we apply the fixed effect regression model to analyse the effect of firm-level ESG score on stock misvaluation. In contrast to the finding in the US stock market, where the ESG score shows a positive relationship with the misvaluation measure, we find the ESG score negatively and significantly affects the misvaluation measure in China. Our findings support that increased disclosure of ESG information enhances information transparency, hence helping investors to value stocks more accurately. We also find that the G score is also negatively related with the misvaluation measure by correcting stock misvaluation from both overvalued and undervalued stocks. Compared with the environmental and social dimensions of ESG that are disclosed only in annual reports, corporate governance information is released in the financial statements as well. The increasing information availability helps firms improve price efficiency. Moreover, a well-established corporate internal structure and governance tend to prioritise long-term value creation and are more likely to exert control over firm valuation.

The significantly negative effects of the ESG and G score on the misvaluation measure are influenced by the extent of ESG and G disclosure. One the one hand, increasing ESG report enhances information transparency. On the other hand, the growing transparency in ESG (G) information may signal to investors that firms with high ESG scores, which actively disclose more ESG (G) information, are in better operational situations. Consequently, investors may be more inclined to buy stocks from these companies, potentially mitigating the undervaluation and strengthens the overvaluation.

Our findings hold for the robustness checks. We rule out the concern of the non-uniformed ESG measures from different data providers and the industry bias concern. We also use the two-stage least squares and dynamic panel GMM models to imitate the endogeneity issue. Overall, the negative and significant effect of the ESG and G score on the misvaluation measure is not affected by these concerns.

Our fourth chapter extends the literature in the ESG performance on firm valuation. This chapter enhances the effect of the main pillars of the ESG score. Our finding indicates that, as well as examining ESG as a whole, further research should also pay attention to the three pillars of ESG individually, as they measure different aspects of firm performance and may have different impacts on stock misvaluation.

The negative effects of the ESG score and G score on stock misvaluation indicate that Chinese government should consider changing the voluntary ESG disclosure requirement to a mandatory disclosure to increase firms' information transparency and, thereby, further improve market price efficiency. Moreover, the E score has comparatively poorer performance than the S and G scores. An insignificant coefficient on the environmental score shows that firms should engage in more activities to improve environmental performances.

Different data providers may affect the ESG data quality, as the methodology used to construct the ESG data is not uniform. When we use the Wind ESG data to examine the effect of the ESG (E, S, G) scores on the misvaluation measure, we find both the ESG score and three pillars affect stock misvaluation. Although this result does not contradict our findings, it indicates that the ESG score provided by different institutions and the length of ESG data may affect the relationship between ESG and stock misvaluation. We suggest the CSRC puts forward a unified ESG constructing method suitable for the Chinese stock market.

CHAPTER FIVE

CONCLUSION

This chapter concludes the thesis by summarising the main findings and implications of each essay.

5.1. Essay One (Chapter Two)

The first essay investigates whether there is evidence of stock misvaluation and an associated risk premium in the Chinese stock market, in which state ownership is a distinct characteristic, compared with the US stock market. We modify the misvaluation estimation method of Rhodes–Kropf et al. (2005) by considering the State-Owned Enterprise (SOEs) and Non-State-Owned Enterprise (Non-SOEs) classification when estimating the intrinsic firm value in the benchmark regression. This ownership classification setting allows accounting variables to capture more within-industry variations of firm value for SOEs than for non-SOEs in the Chinese stock market. We find the misvaluation effect of SOEs is more significant than that of non-SOEs, while the misvaluation correction speed of the former is faster than that of the latter. Furthermore, loadings on stock misvaluation are negatively related to cross-sectional stock returns, implying a stock misvaluation correction. This finding is consistent with Chang et al. (2013)'s investigation in the US stock market. Moreover, we find positive premiums of the misvaluation factor in the Fama Macbeth two-stage regression model. The essay shows evidence that the misvaluation effect of the Chinese stock market is significant.

This essay contributes to the literature by highlighting the influence of the market environment on asset pricing. First, the essay provides evidence of stock misvaluation, while highlighting the difference between SOEs and non-SOEs' effect on misvaluation, unique to the Chinese stock market. Second, the essay extends the work of Chang et al. (2013) by investigating the misvaluation correction speed and making comparisons of the misvaluation effect between SOEs and Non-SOEs. Our results can also be used to highlight the difference between the largest developed and developing markets. Moreover, our result suggest that the effectiveness of the asset pricing method may vary across markets. Researchers should consider new factors affecting firm value based on the specific characteristics of the market under investigation.

5.2. Essay Two (Chapter Three)

The second essay investigates whether, and how, Chinese margin traders and short sellers cause stock misvaluation. Extending the sample period to recent years, we find the positive (cumulative) abnormal returns (around) on the event trading day(s) when stocks become eligible to be purchased on margin and sold short by applying the event study of Chang et al. (2014) on the same issue. Our findings run counter to the negative (cumulative) abnormal returns of Chang et al. (2014), suggesting that the soaring margin-trading activities help incorporate much positive information into stock prices. We construct the MS index and a demeaned MS index, denoted as $\mathrm{MS}^{\mathrm{DM}}$, to further investigate whether imbalanced trading activities between margin trading and short selling affect stock misvaluation. We find the $\mathrm{MS}^{\mathrm{DM}}$ index positively affects stock misvaluation. The index expands overvaluation while reducing undervaluation. This effect is mainly due to the fact that margin-trading activities dominates the total trading volume of the Chinese pilot programme. This fact emerged after the study by Chang et al. (2014). The misvaluation effect of margin-trading activities is in line with that of the $\mathrm{MS}^{\mathrm{DM}}$ index. The essay also reveals that margin-trading activities function to reduce stock undervaluation. This finding is different from that of Chang et al. (2014), who argue margin traders are not information providers. Meanwhile, our finding for short-selling activities is consistent with that of Chang et al. (2014); that is, short sales improve price efficiency by decreasing overvaluation. Moreover, we find recent margin-trading and short-selling activities mitigate the relationship between pilot trading and misvaluation, as the reformed regulations mitigate the imbalanced trading situation.

The second essay contributes to the existing literature by comprehensively investigating the joint influence of both margin-trading and short-selling activities, as well as the associated trading dispersion, on price efficiency. It provides a new angle to explore how the imbalanced trading activities of the Chinese pilot programme can lead to stock misvaluation. We go beyond the work of Chang et al. (2014), and our work generates a new insight that margin traders are the leading players in the Chinese pilot programme. They are information providers. Although margin-trading activities amplify overvaluation, they reduce undervaluation.

The implications of the second essay are outlined as follows. The Chinese regulators should encourage short sales to reduce the trading volume gap with margin-trading activities. Expanding the sources of the securities allowed to be sold short can reduce the size of the group of short sellers who face difficulties borrowing securities in the Chinese stock market. Regulators should also facilitate the participation of a broader range of investors in margin-trading and short-selling activities. This should include a focus on professional investors, such as qualified foreign institutional investors (QFII), who are more inclined towards short selling compared to retail investors who have a purchasing-oriented mindset. However, the second study focuses on the influence of stock-level trading on stock misvaluation without considering the eligible indexes that can be bought on margin and/or sold short. Short sellers may short a portfolio of stocks rather than a single stock. Exploring the effect of eligible indexes on price efficiency is a possible topic for future research.

5.3. Essay Three (Chapter Four)

The third essay examines whether the ESG performance of a firm is associated with stock misvaluation and hence price efficiency. We find that the ESG score is negatively associated with stock misvaluation. The ESG disclosure score is an influence factor in the relationship between the ESG score and misvaluation. Our findings suggest the influence of ESG score on misvaluation could be attributed to information transparency. Furthermore, we find some evidence that the pillars of ESG have different effects on misvaluation, with a negative coefficient sign on the G score and an insignificant coefficient on the E score. S score is positively related with stock overvaluation. We find no evidence that the relationship between the ESG score and stock misvaluation is affected by macroeconomic policy uncertainty.

The third essay contributes to price efficiency literature by examining the influence of non-financial information on stock misvaluation. Non-financial information complements the information sources that investors use to value companies. This study also adds to the strand of literature on ESG by providing a comprehensive study of its three pillars.

The third essay generates several implications for firms and regulators. First, Chinese companies should pay more attention to the development of ESG initiatives, especially ESG information disclosure. A firm with high ESG information disclosure can reduce stock misvaluation by improving information transparency. Second, researchers cannot treat the pillars of ESG as if they were homogeneous with overall ESG, because each of the pillars measures different aspects of a firm's performance and so influences price efficiency in different ways. Ignoring such differences would render researchers' results misleading. Third, Chinese firms should pay more attention to the environmental and social dimensions of ESG, the performance of which is much worse than corporate governance. Lastly, we suggest that the Chinese regulators develop a unified ESG constructing method, as the ESG score of a firm may slightly vary across different ESG data providers. This issue may challenge the relationship between the ESG score and stock misvaluation. Hence, we recommend that researchers utilise diverse data sources for ESG scores when conducting their research.

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APPENDIX A

FOR ESSAY TWO

Appendix A.1. The construction process of alternative misvaluation measure

The alternative measure of stock misvaluation is derived from the residual income model of Ohlson (1995). Based on the assumption of clean surplus, the intrinsic value of a firm could be seen as the sum of the book value and the discounted value of expected residual incomes. Based on the work of Ohlson (1995), Dong et al. (2006) estimate the stock value through predicting an infinite number of future earnings forecasts. We follow Lee et al. (1999) and Dong et al. (2006) and use a three-period forecast horizon. The intrinsic value of a firm $V(t)$ is estimated as:

$$V(t) = B(t) + \frac{[f^{ROE}(t+1) - r_e(t)]B(t)}{1 + r_e(t)} + \frac{[f^{ROE}(t+2) - r_e(t)]B(t+1)}{[1 + r_e(t)]^2} + \frac{[f^{ROE}(t+3) - r_e(t)]B(t+2)}{[1 + r_e(t)]^2 r_e(t)} \tag{1}$$

where $f^{ROE}(t+i)$ is the forecasted return on equity for period $t+i$. i equals 1, 2, 3, with the length of each period being 1 quarter. This last term discounts residual incomes in the period $t+3$ as the perpetuity.

The forecasted return on equity f^{ROE} is calculated as:

$$f^{ROE}(t+i) = \frac{f^{EPS}(t+i)}{\underline{B}(t+i-1)} \tag{2}$$

where f^{ROE} is required to be less than 1 (Dong et al., 2006). $f^{EPS}(t+i)$ is the forecasted earnings per share for period $t+i$. i equals 1, 2, 3. $\underline{B}(t+i-1)$ is computed as:

$$\underline{B}(t+i-1) \equiv \frac{B(t+i-1)+B(t+i-2)}{2} \tag{3}$$

$\underline{B}(t+i-1)$ is calculated as the average of the book value of equity in both period $i-1$ and period $i-2$. The future book value of equity is determined as:

$$B(t+i) = B(t+i-1) + (1-k)f^{EPS}(t+i) \tag{4}$$

k is the firm payout ratio. Following Dong et al. (2020) and Bofinger et al. (2022), we delete firms with payout ratios greater than 1. k is defined as:

$$k = \frac{D(t)}{EPS(t)} \tag{5}$$

$D(t)$ is the firm dividend payment in period t. $EPS(t)$ is the earnings per share in period t. Following Dong et al. (2006), we use a Capital Asset Pricing Model (CAPM) regression to estimate the annualised cost of equity $r_e(t)$. In the framework of CAPM, we estimate the time-t beta by using trailing five years'[46] monthly stock returns. To ensure enough data in the time-series regression, we retain firms with the history of stock trading of more than two years. The market risk premium is the average risk premium of the value-weighted market return over the risk-free rate over the preceding five years. Any estimated cost of equity outside the range of 3-30% is winsorized to this range.

To measure stock misvaluation, we compare the intrinsic value $V(t)$ with the actual market price. The equation is defined as:

$$\mathrm{MSVF}_{\mathrm{Ohlson},i\,t} = \frac{P(i,t)}{V(i,t)} \tag{6}$$

Finally, $\mathrm{MSVF}_{\mathrm{Ohlson}}$ is winsorized at the 1% and 99%. $\mathrm{MSVF}_{\mathrm{Ohlson}}$ measures the misvaluation of a firm. A firm is overvalued when its ratio is higher than 1. While a stock is undervalued when $\mathrm{MSVF}_{\mathrm{Ohlson}}$ is less than 1.

[46] We also use a three-year investment horizon to estimate the time-t beta. Our results remain consistent. For conciseness, we don't report this result.

Appendix A.2. Company misvaluation regressed on the MS^{DM} index – annualised data frequency

Variables	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$	(9) $MSVF_{Chang}$	(10) $MSVF_{Chang}$
Constant	-0.155***	0.133	-0.124	0.133	-1.478***	-0.194***	0.045	-0.182	0.045	-1.582***
	[-266.56]	[0.47]	[-0.38]	[0.47]	[-3.96]	[-636.4]	[0.16]	[-0.56]	[0.15]	[-2.87]
Dep_{-1}	0.308***	0.242***		0.242***	0.061**	0.309***	0.241***		0.241***	0.066**
	[13.22]	[9.51]		[9.51]	[2.17]	[13.26]	[9.26]		[9.26]	[2.14]
MS_{-1}	0.333***	0.188**	0.261***			0.332***	0.165*	0.238**		
	[3.78]	[1.97]	[2.63]			[3.74]	[1.74]	[2.44]		
MT_{-1}				0.19**					0.167*	
				[1.98]					[1.75]	
SS_{-1}					-81.771**					-103.186***
					[-2.34]					[-2.9]
Lev		0.322***	0.303***	0.322***	0.256**		0.284***	0.262**	0.284***	0.253**
		[3.17]	[2.87]	[3.17]	[2.16]		[2.87]	[2.51]	[2.87]	[2.09]
Profitability		-0.592	-0.232	-0.592	-1.379***		-0.662*	-0.323	-0.662*	-1.799***
		[-1.54]	[-0.52]	[-1.54]	[-2.81]		[-1.66]	[-0.7]	[-1.66]	[-3.66]
CapEx		-0.021	-0.011	-0.021	0.043**		-0.019	-0.01	-0.019	0.046**
		[-1.57]	[-0.71]	[-1.57]	[2.53]		[-1.37]	[-0.64]	[-1.37]	[2.24]
Market-to-Book		0.015	0.018	0.015	0.062***		0.016	0.019	0.016	0.063***
		[1.34]	[1.42]	[1.34]	[7.64]		[1.32]	[1.36]	[1.32]	[7.58]
Volatility		1.705*	2.637**	1.702*	1.139		2.047*	2.975**	2.043*	1.334
		[1.66]	[2.26]	[1.66]	[1.15]		[1.9]	[2.39]	[1.9]	[1.32]
Analyst Coverage		0.005***	0.007***	0.005***	0.003***		0.005***	0.007***	0.005***	0.003***
		[7.97]	[8.36]	[7.97]	[5.1]		[7.73]	[8.14]	[7.73]	[4.57]
Obs.	4209	4203	4204	4203	2094	4209	4203	4204	4203	2094
R-square	74.96%	76.77%	75.52%	76.77%	82.03%	74.79%	76.64%	75.41%	76.64%	81.51%

Notes: This table reports the fixed effect estimations of the effect of a firm's annually lagged MS^{DM} index on its respective misvaluation. The dependent variables are misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), taking into consideration the ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix A.3. The misvaluation regressed on margin trading and short selling

Variables	(1) MSVF	(2) $MSVF_{Chang}$
Intercept	0.037	0.274***
	[0.65]	[4.49]
Dep_{-1}	0.791***	0.848***
	[158.12]	[245.24]
MT_{-1}	0.667***	0.714***
	[8.47]	[8.73]
SS_{-1}	-4.127***	-6.203***
	[-3.23]	[-4]
Lev	0.002	0.039**
	[0.12]	[2.13]
Profitability	-0.16***	-0.247***
	[-4.67]	[-6.77]
CapEx	-0.003	-0.016***
	[-1.08]	[-5.23]
Market-to-Book	0.001***	0.001***
	[3.07]	[3.78]
Volatility	2.517***	2.704***
	[24.35]	[24.57]
Analyst Coverage	0.003***	0.002***
	[14.02]	[9.7]
Obs.	62864	62864
R-square	91.10%	92.16%

Notes: This table reports the fixed effect estimations of the effect of margin trading and short selling on its respective misvaluation. The dependent variables are misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), taking into consideration the ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix A.4. The effect of $\mathrm{MS}^{\mathrm{DM}}$ index on misvaluation during the sample period of Chang et al. (2014)

Variables	(1) $\mathrm{MSVF}_{\mathrm{Chang}}$	(2) $\mathrm{MSVF}_{\mathrm{Chang}}$	(3) $\mathrm{MSVF}_{\mathrm{Chang}}$
Constant	0.243***	0.462	1.68
	[18.24]	[0.78]	[1.47]
Dep_{-1}	0.701***	0.59***	
	[37.92]	[25.22]	
$\mathrm{MS}_{-1}^{\mathrm{DM}}$	-16.977***	-14.633***	-6.968***
	[-8.26]	[-7.16]	[-3.09]
Lev		-0.807***	-1.149***
		[-3.74]	[-2.73]
Profitability		-1.004***	-0.998***
		[-5.53]	[-3.43]
CapEx		0.015	-0.018
		[0.57]	[-0.36]
Market-to-Book		0.023***	0.048***
		[5.85]	[6.6]
Volatility		0.288	0.921**
		[1.05]	[2.5]
Analyst Coverage		0	0.003***
		[0.05]	[5.19]
Obs.	1300	1294	1295
R-square	93.48%	94.38%	90.63%

Notes: This table reports the fixed effect estimations of the effect of an eligible firm's lagged $\mathrm{MS}^{\mathrm{DM}}$ index on its respective misvaluation during the data period used by Chang et al. (2014). The dependent variable is the misvaluation measure (MSVF) derived from the method of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix A.5. Lagged control variables test

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) $MSVF_{Chang}$	(6) $MSVF_{Chang}$	(7) $MSVF_{Chang}$	(8) $MSVF_{Chang}$
Intercept	0.195***	-0.776***	0.195***	0.194***	0.344***	-0.453**	0.344***	0.341***
	[3.2]	[-3.81]	[3.2]	[3.18]	[5.3]	[-2.04]	[5.3]	[5.26]
Dep_{-1}	0.767***		0.768***	0.768***	0.772***		0.772***	0.773***
	[122.33]		[122.33]	[124.74]	[112.85]		[112.85]	[113.46]
MS^{DM}_{-1}	0.179*	2.551***			0.269***	1.569***		
	[1.76]	[14.78]			[2.77]	[9.81]		
MT_{-1}			0.173*				0.257***	
			[1.7]				[2.65]	
SS_{-1}				-2.524*				-4.441***
				[-1.75]				[-3.44]
Lev_{-1}	-0.055***	-0.295***	-0.055***	-0.055***	-0.058***	-0.359***	-0.058***	-0.058***
	[-2.95]	[-4.64]	[-2.95]	[-2.96]	[-3.19]	[-6.04]	[-3.19]	[-3.22]
$Profitability_{-1}$	-0.836***	-1.588***	-0.836***	-0.835***	-1.166***	-2.605***	-1.166***	-1.164***
	[-19.72]	[-15.42]	[-19.72]	[-19.74]	[-26.93]	[-27.2]	[-26.93]	[-26.91]
$CapEx_{-1}$	-0.007**	0.045***	-0.007**	-0.007**	-0.017***	0.016	-0.017***	-0.017***
	[-2.26]	[4.35]	[-2.26]	[-2.26]	[-5.19]	[1.46]	[-5.19]	[-5.17]
$Market\_to\_Book_{-1}$	0.006***	0.038***	0.006***	0.006***	0.013***	0.069***	0.013***	0.013***
	[15.02]	[30.1]	[15.03]	[15.03]	[21.56]	[41.3]	[21.56]	[21.51]
$Volatility_{-1}$	0.115	2.751***	0.115	0.14	0.209**	2.945***	0.209**	0.251***
	[1.3]	[15.53]	[1.3]	[1.58]	[2.53]	[16.89]	[2.53]	[3.04]
Analyst Coverage $_{-1}$	-0.001***	0.006***	-0.001***	-0.001***	-0.002***	0.003***	-0.002***	-0.002***
	[-4.33]	[12.25]	[-4.33]	[-4.32]	[-10.34]	[7.04]	[-10.34]	[-10.3]
Obs.	55149	55150	55149	55149	55149	55150	55149	55149
R-square	90.13%	78.71%	90.13%	90.13%	91.40%	81.86%	91.40%	91.40%

Notes: This table reports the fixed effect estimations of the effect of a firm's lagged MS^{DM} index on its respective misvaluation. We take one-period lag into control variables. The dependent variables are misvaluation measures. MSVF is derived from the modified method of Rhodes-Kropf et al. (2005) and Chang et al. (2013), taking into consideration the ownership classification in the benchmark regressions. $MSVF_{Chang}$ is the original misvaluation measure of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Standard errors are clustered at the firm-level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix A.6. The effect of MS^{DM} index on overvaluation and undervaluation during the sample period of Chang et al. (2014)

Variables	(1) $MSVF_{Over}$	(2) $MSVF_{Over}$	(3) $MSVF_{Over}$	(4) $MSVF_{Under}$	(5) $MSVF_{Under}$	(6) $MSVF_{Under}$
Constant	0.376***	-2.027***	-4.039***	-0.106***	-2.294***	-2.54***
	[17.54]	[-2.7]	[-6.56]	[-14.64]	[-3.42]	[-3.12]
Dep_{-1}	0.517***	0.402***		0.521***	0.446***	
	[16.55]	[14.02]		[16.93]	[11.55]	
MS_{-1}^{DM}	-4.565*	-6.118***	-4.1*	-2.191	-2.984	0.796
	[-1.88]	[-2.79]	[-1.74]	[-0.81]	[-1.54]	[0.27]
Lev		-0.6***	-0.945***		0.003	-0.025
		[-3.05]	[-5.77]		[0.01]	[-0.1]
Profitability		-1.268***	-1.996***		-0.56	-0.372
		[-6.44]	[-10.59]		[-1.18]	[-0.63]
CapEx		0.124***	0.233***		0.082***	0.084**
		[3.6]	[8.23]		[2.71]	[2.36]
Market-to-Book		0.023***	0.046***		0.11***	0.145***
		[6.5]	[18.85]		[8.62]	[9.32]
Volatility		-0.164	-3.093***		1.552	1.566
		[-0.64]	[-3.59]		[1.63]	[1.4]
Analyst Coverage		0.002***	0.006***		0.001	0.002
		[3.62]	[5.73]		[0.69]	[1.5]
Obs.	1399	1393	1013	578	572	573
R-square	84.97%	88.61%	84.65%	86.97%	90.33%	84.36%

Notes: This table reports the fixed effect estimations of the effect of an eligible firm's lagged MS^{DM} index on its respective misvaluation during the data period used by Chang et al. (2014). The dependent variable is the misvaluation measure (MSVF) derived from the method of Rhodes-Kropf et al. (2005) and Chang et al. (2013). Models 1,2,3 show the results of the overvaluation group. Models 4,5,6 show the results of the undervaluation group. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

APPENDIX B

FOR ESSAY THREE

Appendix B.1. Fixed effect regression results incorporating MS_{-1}^{DM} index

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.145	1.089	0.799	0.907
	[1.05]	[0.94]	[0.72]	[0.83]
Dep_{-1}	-0.327***	-0.334***	-0.327***	-0.332***
	[-5.74]	[-5.8]	[-5.72]	[-5.82]
$ESG\ Score_{-1}$	-0.076***			
	[-3.3]			
$E\ Score_{-1}$		-0.011		
		[-1.33]		
$S\ Score_{-1}$			-0.021***	
			[-3.28]	
$G\ Score_{-1}$				-0.013***
				[-3.4]
MS_{-1}^{DM}	1.022*	0.983*	1.037*	0.923*
	[1.86]	[1.78]	[1.89]	[1.66]
Lev	0.562*	0.558*	0.506*	0.537*
	[1.92]	[1.88]	[1.71]	[1.83]
Profitability	-2.303***	-2.282***	-2.416***	-2.417***
	[-3.57]	[-3.39]	[-3.7]	[-3.71]
CapEx	-0.055	-0.073	-0.056	-0.062
	[-1.07]	[-1.37]	[-1.11]	[-1.23]
Market-to-Book	0.03*	0.027	0.032*	0.032*
	[1.71]	[1.43]	[1.81]	[1.82]
Volatility	5.05*	5.544**	4.439*	4.304
	[1.89]	[2.07]	[1.66]	[1.59]
Analyst Coverage	-0.033	-0.029	-0.035	-0.034
	[-1.36]	[-1.21]	[-1.46]	[-1.4]
Firm-year obs.	781	781	781	781
R-square	90.31%	90.20%	90.32%	90.32%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on lagged ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. We include MS_{-1}^{DM} as an additional control variable into regressions. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix B.2. Changes of stock misvaluation regressed on changes of ESG score, E score, Score, G score

	(1) MSVF_{Change}	(2) MSVF_{Change}	(3) MSVF_{Change}	(4) MSVF_{Change}
Intercept	1.793***	1.792***	1.791***	1.799***
	[8.29]	[8.27]	[8.27]	[8.32]
Dep_{-1}	-0.352***	-0.352***	-0.351***	-0.352***
	[-40.66]	[-40.64]	[-40.61]	[-40.7]
$\text{ESG Score}_{Change}$	-0.16*			
	[-1.71]			
E Score_{Change}		-0.042		
		[-0.57]		
S Score_{Change}			0.022	
			[0.53]	
G Score_{Change}				-0.171**
				[-2.42]
Lev	0.275***	0.275***	0.275***	0.273***
	[4.43]	[4.43]	[4.42]	[4.4]
Profitability	-3.587***	-3.588***	-3.587***	-3.582***
	[-13.86]	[-13.85]	[-13.85]	[-13.84]
CapEx	-0.1***	-0.1***	-0.1***	-0.1***
	[-9.31]	[-9.29]	[-9.29]	[-9.31]
Market-to-Book	0.003**	0.003**	0.003**	0.003**
	[2]	[2.03]	[2.04]	[1.98]
Volatility	-0.888***	-0.883***	-0.878***	-0.872***
	[-2.89]	[-2.87]	[-2.85]	[-2.84]
Analyst Coverage	-0.044***	-0.044***	-0.044***	-0.044***
	[-8.52]	[-8.52]	[-8.52]	[-8.5]
Firm-year obs.	12674	12674	12674	12674
R-square	25.34%	25.32%	25.32%	25.37%

Notes: This table shows the fixed effect regression results of changes of stock misvaluation (MSVF) regressed on changes of ESG score and E, S, G scores in models 1, 2, 3 and 4, respectively. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix B.3. Stock misvaluation regressed on ESG score, E score, S score, G score - median value of misvaluation

Panel A: Most overvalued firms > median of MSVF					Panel B: Most undervalued firms < median of MSVF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF	MSVF
Intercept	1.314***	1.316***	1.267***	1.457***	0.589***	0.671***	0.645***	0.43***
	[7.21]	[7.81]	[7.58]	[8.04]	[4.25]	[5.25]	[5.06]	[3.07]
Dep_{-1}	0.174***	0.174***	0.174***	0.173***	0.137***	0.136***	0.136***	0.137***
	[12.19]	[12.21]	[12.21]	[12.13]	[10.77]	[10.71]	[10.71]	[10.84]
ESG Score_{-1}	0.011				0.04			
	[0.09]				[0.51]			
E Score_{-1}		0.013				-0.147***		
		[0.14]				[-2.6]		
S Score_{-1}			0.132**				-0.061*	
			[2.1]				[-1.66]	
G Score_{-1}				-0.16*				0.171***
				[-1.83]				[3.17]
Lev	0.21***	0.21***	0.208***	0.206***	0.084**	0.081**	0.084**	0.088**
	[3.69]	[3.69]	[3.67]	[3.63]	[2.33]	[2.24]	[2.33]	[2.44]
Profitability	-1.241***	-1.241***	-1.227***	-1.245***	-0.476	-0.476	-0.479	-0.471
	[-5.06]	[-5.07]	[-5]	[-5.08]	[-1.16]	[-1.16]	[-1.17]	[-1.15]
CapEx	-0.053***	-0.053***	-0.055***	-0.054***	-0.048***	-0.046***	-0.046***	-0.046***
	[-6.19]	[-6.19]	[-6.42]	[-6.29]	[-7.24]	[-7.06]	[-7.05]	[-7.07]
Market-to-Book	0.005***	0.005***	0.005***	0.005***	0.01***	0.01***	0.01***	0.01***
	[2.8]	[2.79]	[2.82]	[2.79]	[4.15]	[4.19]	[4.15]	[4.06]
Volatility	-0.201	-0.203	-0.187	-0.191	0.424	0.426	0.419	0.414
	[-0.3]	[-0.3]	[-0.27]	[-0.29]	[1.58]	[1.59]	[1.56]	[1.54]
Analyst Coverage	0.009	0.009	0.009	0.01*	0.023***	0.022***	0.023***	0.022***
	[1.53]	[1.54]	[1.55]	[1.68]	[5.7]	[5.65]	[5.69]	[5.44]
Firm-year obs.	8140	8140	8140	8140	8290	8290	8290	8290

R-square	55.58%	55.58%	55.61%	55.6%	45.93%	45.98%	45.95%	46.02%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores for over- and undervalued stocks. We define a stock as overvalued when its stock misvaluation is greater than the median value of the sample in the respective year. A stock is defined as undervalued when its stock misvaluation is smaller than the median value of the sample in the respective year. Models (1) to (4) of Panel A represent the analyses for overvalued stocks. Models (5) to (8) of Panel B represent the analyses for undervalued stocks. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix B.4. Stock misvaluation regressed on ESG score, E score, S score, G score - using positive (negative) sign of misvaluation

Panel A: Most overvalued firms - positive MSVF					Panel B: Most undervalued firms - negative MSVF			
	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF	(5) MSVF	(6) MSVF	(7) MSVF	(8) MSVF
Intercept	1.257***	1.233***	1.184***	1.421***	0.457***	0.518***	0.491***	0.346***
	[7.15]	[7.62]	[7.42]	[8.24]	[3.56]	[4.37]	[4.17]	[2.68]
Dep_{-1}	0.177***	0.177***	0.177***	0.176***	0.137***	0.136***	0.136***	0.137***
	[12.08]	[12.12]	[12.11]	[11.99]	[11.05]	[10.99]	[11]	[11.11]
ESG $Score_{-1}$	0				0.021			
	[0]				[0.28]			
E $Score_{-1}$		0.06				-0.126**		
		[0.67]				[-2.24]		
S $Score_{-1}$			0.164***				-0.042	
			[2.74]				[-1.17]	
G $Score_{-1}$				-0.199**				0.116**
				[-2.29]				[2.22]
Lev	0.209***	0.21***	0.206***	0.203***	0.105***	0.102***	0.105***	0.108***
	[3.67]	[3.69]	[3.63]	[3.58]	[2.96]	[2.89]	[2.97]	[3.04]
Profitability	-1.012***	-1.008***	-0.991***	-1.018***	-0.456	-0.457	-0.459	-0.453
	[-4.59]	[-4.57]	[-4.49]	[-4.62]	[-1.12]	[-1.12]	[-1.12]	[-1.11]
CapEx	-0.049***	-0.049***	-0.051***	-0.05***	-0.04***	-0.039***	-0.039***	-0.039***
	[-6.05]	[-6.11]	[-6.32]	[-6.15]	[-6.66]	[-6.51]	[-6.51]	[-6.53]
Market-to-Book	0.002***	0.002***	0.002***	0.002***	0.009***	0.009***	0.009***	0.009***
	[5.04]	[5.05]	[5.03]	[5.01]	[4.22]	[4.27]	[4.23]	[4.13]
Volatility	-0.183	-0.189	-0.167	-0.171	0.467*	0.469*	0.463*	0.459*
	[-0.42]	[-0.43]	[-0.37]	[-0.39]	[1.79]	[1.8]	[1.78]	[1.76]
Analyst Coverage	0.006	0.006	0.006	0.007	0.02***	0.02***	0.02***	0.019***
	[1.07]	[1.09]	[1.06]	[1.24]	[5.19]	[5.14]	[5.19]	[5]
Firm-year obs.	8097	8097	8097	8097	8286	8286	8286	8286

R-square	54.89%	54.89%	54.94%	54.93%	45.77%	45.81%	45.78%	45.81%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the lagged ESG score and E, S, G scores for over- and undervalued stocks. We define a stock as overvalued when its stock misvaluation is positive. A stock is defined as undervalued when its stock misvaluation is negative. Models (1) to (4) of Panel A represent the analyses for overvalued stocks. Models (5) to (8) of Panel B represent the analyses for undervalued stocks. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.

Appendix B.5: Influencing role of information asymmetry

Panel Influencing role of earnings forecast error

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.312*** [8.19]	1.223*** [8.33]	1.172*** [7.98]	1.338*** [8.29]
Dep_{-1}	0.327*** [28.19]	0.327*** [28.22]	0.328*** [28.29]	0.327*** [28.19]
$\mathrm{ESG\ Score}_{-1}$	-0.186** [-2.08]			
Earnings FE	-0.536 [-1.22]			
$\mathrm{ESG\ Score}_{-1} \times$ Earnings FE	0.653 [1.1]			
$\mathrm{E\ Score}_{-1}$		-0.114* [-1.66]		
Earnings FE		-0.372 [-1.52]		
$\mathrm{E\ Score}_{-1} \times$ Earnings FE		0.521 [1.31]		
$\mathrm{S\ Score}_{-1}$			0.014 [0.32]	
Earnings FE			-0.105 [-0.49]	
$\mathrm{S\ Score}_{-1} \times$ Earnings FE			0.062 [0.21]	
$\mathrm{G\ Score}_{-1}$				-0.153** [-2.33]
Earnings FE				-0.351 [-0.89]
$\mathrm{G\ Score}_{-1} \times$ Earnings FE				0.367 [0.76]
Lev	0.251*** [5.64]	0.253*** [5.66]	0.253*** [5.68]	0.249*** [5.59]
Profitability	-1.863*** [-10.08]	-1.86*** [-10.07]	-1.858*** [-10.05]	-1.866*** [-10.1]
CapEx	-0.074*** [-9.86]	-0.074*** [-9.82]	-0.075*** [-9.95]	-0.075*** [-9.99]
Market-to-Book	0.003 [1.07]	0.003 [1.06]	0.003 [1.06]	0.003 [1.07]
Volatility	0.279 [0.77]	0.299 [0.82]	0.287 [0.79]	0.283 [0.77]
Analyst Coverage	0.031*** [7.42]	0.031*** [7.3]	0.031*** [7.34]	0.032*** [7.52]
Firm-year obs.	18399	18399	18399	18399

R-square	63.19%	63.19%	63.18%	63.19%

Panel B Influencing role of illiquidity

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	0.929***	0.878***	0.807***	0.965***
	[5.97]	[6.09]	[5.76]	[6.09]
Dep_{-1}	0.303***	0.303***	0.304***	0.302***
	[27.63]	[27.68]	[27.76]	[27.59]
ESG Score_{-1}	-0.189*			
	[-1.89]			
illiquidity	0.321			
	[0.04]			
$\text{ESG Score}_{-1} \times$ illiquidity	5.015			
	[0.44]			
E Score_{-1}		-0.172**		
		[-2.27]		
illiquidity		-5.448		
		[-1.07]		
$\text{E Score}_{-1} \times$ illiquidity		16.02*		
		[1.86]		
S Score_{-1}			-0.018	
			[-0.35]	
illiquidity			-2.986	
			[-0.75]	
$\text{S Score}_{-1} \times$ illiquidity			9.947*	
			[1.76]	
G Score_{-1}				-0.151**
				[-2.09]
illiquidity				8.668
				[1.28]
$\text{G Score}_{-1} \times$ illiquidity				-5.84
				[-0.7]
Lev	0.16***	0.161***	0.162***	0.156***
	[4.02]	[4.03]	[4.07]	[3.92]
Profitability	-1.988***	-1.982***	-1.984***	-1.985***
	[-10.75]	[-10.71]	[-10.72]	[-10.73]
CapEx	-0.054***	-0.054***	-0.055***	-0.056***
	[-7.44]	[-7.42]	[-7.49]	[-7.66]
Market-to-Book	0.018***	0.018***	0.018***	0.018***
	[8.43]	[8.45]	[8.4]	[8.46]
Volatility	-0.893***	-0.911***	-0.91***	-0.869***
	[-3.08]	[-3.13]	[-3.14]	[-3]
Analyst Coverage	0.028***	0.028***	0.028***	0.029***
	[7.02]	[6.9]	[6.97]	[7.23]
Firm-year obs.	18399	18399	18399	18399
R-square	63.63%	63.63%	63.63%	63.64%

Panel C Influencing role of Bid-ask spread

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	0.981***	0.845***	0.786***	0.946***
	[5.52]	[5.62]	[5.51]	[5.61]
Dep_{-1}	0.31***	0.31***	0.311***	0.31***
	[24.9]	[24.96]	[25.02]	[24.89]
$\mathrm{ESG\ Score}_{-1}$	-0.331**			
	[-2.02]			
Bid_ask	5.035			
	[1.5]			
$\mathrm{ESG\ Score}_{-1} \times \mathrm{Bid\_ask}$	3.659			
	[0.81]			
$\mathrm{E\ Score}_{-1}$		-0.201*		
		[-1.73]		
Bid_ask		5.587***		
		[2.78]		
$\mathrm{E\ Score}_{-1} \times \mathrm{Bid\_ask}$		3.498		
		[1.07]		
$\mathrm{S\ Score}_{-1}$			-0.065	
			[-0.82]	
Bid_ask			6.447***	
			[4.07]	
$\mathrm{S\ Score}_{-1} \times \mathrm{Bid\_ask}$			1.7	
			[0.79]	
$\mathrm{G\ Score}_{-1}$				-0.199*
				[-1.67]
Bid_ask				6.841**
				[2.52]
$\mathrm{G\ Score}_{-1} \times \mathrm{Bid\_ask}$				1.078
				[0.32]
Lev	0.238***	0.24***	0.241***	0.235***
	[5.59]	[5.64]	[5.68]	[5.53]
Profitability	-1.044***	-1.038***	-1.037***	-1.042***
	[-2.86]	[-2.85]	[-2.85]	[-2.86]
CapEx	-0.066***	-0.066***	-0.067***	-0.068***
	[-9.62]	[-9.64]	[-9.67]	[-9.86]
Market-to-Book	0.002***	0.002***	0.002***	0.002***
	[6.07]	[5.99]	[6.01]	[6.16]
Volatility	0.098	0.098	0.091	0.108
	[0.36]	[0.36]	[0.33]	[0.39]
Analyst Coverage	0.03***	0.029***	0.029***	0.03***
	[6.7]	[6.56]	[6.55]	[6.81]
Firm-year obs.	18399	18399	18399	18399
R-square	64.26%	64.25%	64.25%	64.27%

Panel D Influencing role of Earnings SD

	(1) MSVF	(2) MSVF	(3) MSVF	(4) MSVF
Intercept	1.308***	1.219***	1.185***	1.34***
	[8.2]	[8.33]	[8.1]	[8.28]
Dep_{-1}	0.327***	0.327***	0.328***	0.327***
	[28.2]	[28.21]	[28.29]	[28.19]
ESG $Score_{-1}$	-0.161*			
	[-1.89]			
Earnings SD	-0.001			
	[-0.03]			
ESG $Score_{-1} \times$ Earnings SD	0.006			
	[0.08]			
E $Score_{-1}$		-0.081		
		[-1.24]		
Earnings SD		0.027		
		[1.04]		
E $Score_{-1} \times$ Earnings SD		-0.043		
		[-0.95]		
S $Score_{-1}$			0.016	
			[0.36]	
Earnings SD			0.002	
			[0.09]	
S $Score_{-1} \times$ Earnings SD			0.001	
			[0.04]	
G $Score_{-1}$				-0.136**
				[-2.18]
Earnings SD				0.048
				[0.99]
G $Score_{-1} \times$ Earnings SD				-0.056
				[-0.94]
Lev	0.251***	0.252***	0.253***	0.249***
	[5.62]	[5.63]	[5.66]	[5.58]
Profitability	-1.869***	-1.865***	-1.86***	-1.867***
	[-10.1]	[-10.08]	[-10.04]	[-10.09]
CapEx	-0.075***	-0.075***	-0.076***	-0.076***
	[-9.94]	[-9.88]	[-10.03]	[-10.12]
Market-to-Book	0.003	0.003	0.003	0.003
	[1.06]	[1.06]	[1.06]	[1.07]
Volatility	0.301	0.306	0.297	0.313
	[0.85]	[0.85]	[0.83]	[0.88]
Analyst Coverage	0.031***	0.03***	0.03***	0.031***
	[7.3]	[7.16]	[7.2]	[7.38]
Firm-year obs.	18399	18399	18399	18399
R-square	63.18%	63.17%	63.17%	63.18%

Notes: This table shows the fixed effect regression results of stock misvaluation (MSVF) regressed on the ESG (E, S, G) score as well as the information asymmetry measures. Panels A, B, C and D report the influencing effect of earnings forecast error, earnings forecast standard deviation, illiquidity and bid-ask spread, respectively. Standard errors are clustered at the firm level. The t-statistics are reported in the parentheses. ***, **, * denote 1%, 5%, 10% significance levels.