Essays on Individual Stock Returns Predictability

A thesis presented in fulfillment of the requirement for the degree of

Doctor of Philosophy

in

Finance

at Massey University, Albany,

New Zealand.

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2022

Abstract

This dissertation considers different aspects of individual stock predictability.

The first essay shows that the previously documented predictability of macroeconomic and technical variables for market returns is also evident in individual stock returns. Technical variables generate better predictability on firms with high limits to arbitrage (small, illiquid, volatile firms), while macroeconomic variables better predict firms with low limits to arbitrage. Technical predictors show a stronger predictive power for high limits to arbitrage firms across the business cycle, whereas macroeconomic variables capture more predictive information for firms with low limits to arbitrage during recessions.

The second essay shows that 14 widely documented technical indicators explain cross-sectional expected returns. The technical indicators have lower estimation errors than the three-factor Fama-French model and historical mean. The long-short portfolios based on cross-sectional estimated returns consistently generate substantial profits across the entire period. The well-known cross-sectional expected return determinants, including momentum, size, book-to-market, investment, and profitability, do not explain the explanatory power of technical indicators. Our findings suggest that technical indicators play an important role in determining the variation in cross-sectional expected returns in addition to the five-factor model.

In the third essay, we use firm characteristics to estimate the enduring momentum probabilities for past winners (losers) to continue to be future winners (losers). The enduring momentum probability is significantly related to stock return persistence and explains cross-sectional expected returns. In addition, it contains different information from momentum signals. Combining the two pieces of information generates an enduring momentum strategy that produces a 2.19% return per month, almost doubling the momentum return. Factors that drive the price momentum strategy, such as seasonality, limit to arbitrage, and transaction costs, do not fully capture the performance of the enduring momentum strategy.

Acknowledgements

First and foremost, I want to express my gratitude to Almighty God for giving me power and confidence throughout the whole PhD process. I take this opportunity to appreciate many people who gave me their unwavering support during my PhD journey.

I would like to express my deep gratitude to my three supervisors, Professor Nuttawat Visaltanachoti, Professor Nhut (Nick) Hoang Nguyen, and Professor Ben Marshall, for their invaluable guidance, support, and encouragement. They are not only my supervisors but also wise mentors throughout my PhD study, and the positive impact will last my whole life. I am especially indebted to my main supervisor - Professor Nuttawat Visaltanachoti, for his patience and comprehension guidance. He has commendable knowledge and a high degree of professionalism and was always very patient in answering my research questions in a very simple and understandable way. I especially appreciate his open-door policy, which enables us to ask him questions whenever he is free at the office. My very special gratitude is also expressed to Professor Nhut (Nick) Hoang Nguyen, who is like my father, strict outside but very soft inside. He always encourages me to work proactively and independently. Moreover, he uses his behaviour to teach me that academic research should be rigorous and detail oriented. I also want to express my sincere appreciation to Professor Ben Marshall, for his useful advice, prompt responses, and gentle corrections. He always encouraged me with every little improvement. Because of their continuous encouragement, patience, and guidance, I was able to go through this journey. I always feel so blessed that I have them as my supervisors.

My appreciation also goes to the financial support I received from the Massey University Conference Presentation Grant for the financial support which has enabled me to attend international conferences. I am also grateful to the discussants and participants at my confirmation and the conferences I attended, for they provided constructive comments and suggestions on my research work. I would like to express my special thanks to Associate Professor Iqbal, Professor Xiaoming Li, Associate Professor Hung Do and Dr Harvey Nguyen for all the teaching and research assistant opportunities. I am also very thankful to Muharram Azizova and Myrah Corrales for generous administrative support and Mark Woods for his excellent IT support. Furthermore, gratitude is extended to Professor Martin Berka, the Head of School, and Professor Sasha Molchanov, the Associate Head of School, for providing all the necessary administrative support.

I would also like to thank all my PhD fellows, particularly Dr Saba Sehrish, Dr Tiantian Tang, Dr Narongdech Thakerngkiat, Dr Feng Yue, Yasmine Farzami, Qinghe Zhao, and Yantao Wen, for their wonderful friendship and support throughout my doctoral studies. They made my PhD life both more enjoyable and colorful. Special thanks to my friend in New Zealand, Kawa, Yangyang Wu, Ran Zhang, Jeff, and Annett, for helpful advice, help, and heartful prayer for me.

I would like to thank my grandparents wholeheartedly, Huaying Jiang, Huajian Zeng, my parents, Shuhua Zhang, Jingjun Zeng, my parents in law, Xuemei Zhang, Binzheng Wu, my sisters and brother, Qian Zeng, Peng Zeng, my aunts, Liru Zeng and Hongming Zhang, my cousins, Tingya Zeng, and all my rest family members, for their endless support and unconditional love throughout my life. Finally, I would like to express my tremendous gratitude to my husband, Qian Wu, and my little son, Hongjun Wu, for their unconditional love and support. Thank God for giving me this most treasurable gift (Hongjun Wu) during the Covid time. He let me become braver and more peaceful than ever before. Thanks to my husband! We accompanied each other through peaks and valleys since our master's study at the University of York, UK. Because of him, to make me brave and this journey possible. My love for them is unquantifiable.

Thank you all, and all the best wishes to all of you!

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CHAPTER ONE: Introduction

This chapter provides a general overview of the three essays included in this thesis. In particular, it outlines each essay's primary motivation, objectives, and contributions to the literature. The organization of this thesis is outlined at the end of this chapter.

1.1. Background of the Study

Over the past few decades, numerous studies have documented that stock returns are predictable. Compared with aggregate market and industry analyses, firm-level return prediction has received less attention. However, the predictability of individual stock returns plays a vital role for various participants in the financial market, such as fund managers who attempt to enhance their investment performance (Falbo and Pelizzari, 2011), risk-averse investors who are motivated to better allocate funds between individual stocks and riskless assets (Kandel and Stambaugh, 1996; Lo and MacKinlay, 1997), and firm managers who seek to improve the estimation accuracy for the firm-level implied cost of capital (Mohanram and Gode, 2013). Jagedeesh and Titman (1993) suggest that past price information of individual firms generates useful information to construct investment portfolios; buying firms in the top decile with higher past returns and selling industrial firms in the bottom decile with lower past performance generate significant positive spread portfolio returns.

Overall, this thesis is primarily motivated by two strands of literature. The first is the asset pricing literature on time series and the cross-sectional context. Predictability in financial markets can be divided into different components: market level, portfolio level, industry level, and individual level. Market-level research has received the most attention compared to other segments, whereas firm-level research has received the least attention. Macroeconomic variables and technical indicators are the two prominent documented candidate predictors of aggregate market-level predictions. Theoretically, macroeconomic variables that track economic activities should be able to predict stock return movements.

In contrast, proponents of technical analysis believe past prices and volume patterns contain prediction information for future stock returns (Brock, Lakonishok, and LeBaron, 1992; Neely, Rapach, Tu, and Zhou, 2014). However, whether well-documented macroeconomic variables and technical indicators can generate significant firm-level predictive information at the firm level prediction remains under-investigated. Therefore, this thesis comprehensively examines their predictive performance in forecasting individual stock returns in both time series and cross-sectional content. In addition, this thesis finds that both macroeconomic and technical indicators generate significant predictive information for firm-level predictability, and that technical indicators perform well in explaining the cross-sectional stock returns.

The second strand of literature concerns investment strategy. Jegadeesh and Titman (1993) find that stock prices display short-term momentum over periods of six months and that portfolios constructed by buying top decile firms with the highest past returns and selling bottom decile firms with the lowest past returns generate significant profits. Many researchers attempt to explain this phenomenon and find that some firm characteristics are related to anomalies generated by the price momentum strategy. The third essay of this thesis utilizes the information of 37 firm characteristics to estimate the probabilities for past winners and losers to survive as winners and losers over the holding period and construct an enhanced investment momentum strategy based on the estimated probabilities.

The remainder of this chapter is organized as follows. Section 1.2 to Section 1.4 provides an overview of essays one, two, and three, respectively, and illustrate how each essay contributes to the literature. The research outputs are presented in Section 1.5. Finally, Section 1.6 outlines the sequence of the remainder of this thesis.

1.2. Essay One

The first essay of this thesis examines the predictive ability of 14 well-documented aggregate macroeconomic and 14 firm-level technical factors in forecasting individual stock returns and whether their predictive performance changes in accordance with firms with different degrees of limits to arbitrage and different market states.

Different studies utilize different macroeconomic variables and technical indicators to predict aggregate stock returns. Candidate macroeconomic variables include dividends (Ball, 1978; Rozeff, 1984; Campbell, 1987), earnings (Campbell and Shiller, 1998, Lamont, 1998), book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), and long-term government bond yield (Fama and French, 1989). Technical indicator followers believe that past price and volume patterns contain useful information for future price trends. Most existing related studies focus on analyzing the role of filter rules (Fama and Blume, 1966), automated pattern recognition (Lo, Mamaysky, and Wang 2000), the trend-following strategies momentum (Conrad and Kaul, 1998; Ahn, Conrad, and Dittmar, 2003) and moving average (Brock, Lakonishok, and LeBaron, 1992; Zhu and Zhou 2009).

Goyal and Welch (2008) comprehensively examine the well-documented 14 macroeconomic variables and find that they fail to outperform the historical mean model in predicting the aggregate market. Neely, Rapach, Tu, and Zhou (2014) comprehensively test the predictive performance of 14 well-documented trend-following technical indicators and find that they play a significant role in forecasting the aggregate market. This thesis applies the well-documented 14 aggregate macroeconomic variables and 14 firm-level technical indicators to firm-level predictability and finds that both of them display significant predictive ability in forecasting firm-level stock returns. However, considering the limits of arbitrage effects, macroeconomic variables show stronger predictive ability for firms with lower limits to arbitrage, whereas technical indicators better detect firms with higher limits of arbitrage.

Furthermore, this essay documents the predictive ability of macroeconomic variables and technical indicators across different economic statuses. The results show that both macroeconomic variables and technical indicators display good predictive ability across the entire business cycle. In addition, macroeconomic variables perform comparatively better in recessions, whereas technical indicators do not have very different predictive performances across economic statuses. Moreover, macroeconomic variables can better predict low arbitrage constraint firms in recessions, whereas technical indicators can explain variations in stock returns for high limits to arbitrage firms across the business cycle, and even better in recessions.

1.3. Essay Two

The classical capital asset pricing model (CAPM) suggests that a firm’s beta significantly influences its expected returns. Subsequently, hundreds of studies investigate other candidate explanatory variables to explain the cross-section of expected returns. For example, the well-known three-factor model (Fama and French, 1993) suggests that the book-to-market ratio and firm size play an important role alongside beta in explaining returns. In 2015, Fama and French extend the three-factor model to the five-factor model by adding profitability and investment factors. The second essay examines whether technical indicators contain the explanatory ability of cross-sectional expected returns and compares this ability with the well-known cross-sectional determinant.

Technical analysis is ubiquitous among practitioners and academics, and most researchers utilize it to predict stock returns on time-series patterns. However, to date, little is known about how technical indicators perform in explaining the cross-sectional stock returns. This study closes this research gap by ascertaining the 14 most documented individual technical indicators using the smoothed ordinary least squares (SOLS) model to explain the cross-sectional expected stock returns. The results show that technical indicators can explain the cross-section of stock returns well and generate lower estimation errors than the Fama-French three-factor and historical mean models. Moreover, the positive and significant time-series and cross-sectional out-of-sample R_{OS}^2 statistics suggest that this SOLS model outperforms the historical mean model.

Furthermore, this essay examines whether the cross-sectional returns estimation information captured by technical indicators is relative to the five well-known cross-sectional stock returns determinants: momentum, size, book-to-market ratio, operating profits, and investment. This essay utilizes Hou and Loh's (2016) variance decomposition method, and the results suggest that technical indicators provide independent information in explaining cross-sectional stock returns, not shared by any of the five well-known firm characteristics.

1.4. Essay Three

Jegadeesh and Titman (1993) demonstrate that stock prices display short-term momentum over six months, and a portfolio constructed by buying top decile firms with the highest past returns and selling bottom decile firms with the lowest past returns generates significant profits. Many researchers attempt to explain this phenomenon, and some find that specific firm characteristics are correlated with future expected returns, which can be used to create an enhanced momentum strategy (Sagi and Seasholes, 2007; Huang, Zhang, Zhou, and Zhu, 2019). Sagi and Seasholes (2007) indicate that some firm characteristics help understand future expected returns and can be used to create enhanced momentum strategies.

Sagi and Seasholes (2007) argue that not all firms exhibit momentum, and understanding future expected returns based on past returns and observable firm-specific attributes helps create enhanced momentum strategies. After evaluating the performance of all past winners and losers, we find that only a small portion of past winners (6.46%) and past losers (5.60%) remain in their positions throughout the following six-month investment periods, and the average enduring months is two for both past winners and losers. Therefore, this essay aims to identify past winners and losers with higher enduring probabilities over the six-month holding period and constructs an enhanced enduring momentum strategy based on past winners/losers with higher enduring probabilities.

Utilizing information on 37 firm characteristics in the Cox hazard model, this essay estimates the survival probabilities for all past winners/losers to continue being winners/losers in the next six-month holding period. The continued momentum portfolio is constructed by buying the top ten firms from past winners with the highest continued probability as winners and selling the top ten firms from past losers with the highest continued probability as losers. The results show that the continued momentum probabilities are significantly related to the persistence of stock returns and play an important role in predicting cross-sectional stock returns. Moreover, the continued strategy generates significantly higher profit than the traditional price momentum, which cannot be explained by the well-known CAPM, three-factor, and Carhart four-factor models.

1.5. Research Outputs from the Thesis

Essay one

The first essay contained in this thesis is published in *Australian Journal of Management*: Zeng, H., Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2021). Are individual stock returns predictable?. *Australian Journal of Management*, 03128962211001509.

1.6. The Sequence of the Thesis

The remainder of this thesis is structured as follows. Chapter 2 presents the first essay, which examines the predictive ability of aggregate macroeconomic variables and firm-level technical indicators in forecasting individual stock returns. Chapter 3 explores how the 14 widely documented technical indicators perform in explaining the cross-sectional stock expected returns. Chapter 4 uses firm characteristics to estimate the enduring momentum probability for past winners (losers) to continue to be the future winners (losers) and constructs the enduring momentum strategy by buying (selling) firms with higher enduring probability as winners (losers). Finally, the key findings and implications of the three essays are outlined in Chapter 5. Suggestions for potential areas of future research are also presented in this last chapter.

CHAPTER TWO: Are Individual Stock Returns Predictable?

As pointed out in the introduction of the thesis, numerous studies have documented that stock returns are predictable. Macroeconomic variables and technical indicators are the most-documented predictors. Compared with the aggregate and industry market, firm-level predictability receives much less attention. However, understanding the predictability of individual stock returns becomes increasingly important. Therefore, the first essay examines the individual stock return determinants and explores whether the predictability of individual stock returns varies across different limits of arbitrage.

2.1. Introduction

Macroeconomic variables and technical indicators are predictors of market-level equity returns (e.g., Goyal and Welch, 2008; Brock, Lakonishok, and LeBaron, 1992). Neely, Rapach, Tu, and Zhou (2014, NRTZ hereafter) show that these variables complement each other in the market risk premium prediction. We contribute to the literature by considering the predictive ability of aggregate macroeconomic and firm-level technical factors for individual stock returns[1] and examine whether the predictability varies with the degree of limits to arbitrage in different stocks and changes through time.

Forecasting individual stock returns provide critical insight into the estimation of a firm's cost of capital and asset allocation. For example, Botosan, Plumlee, and Wen (2011) find that the implied cost of capital (ICC) estimates are significantly correlated to future

[1] While the majority of papers consider predictability using market returns, many authors (including Lee and Swaminathan (2000), Jegadeesh and Titman (2001) for technical factors and Boudoukh, Michaely, Richardson, and Roberts (2007) and Mookerjee and Yu (1997) for fundamental factors) have considered individual stock returns.

returns. Christensen, Feltham, and Wu (2002) claim that firm managers face significant firm-specific risk in calculating the cost of capital when making investment decisions, while Mohanram and Gode (2013) find that removing predictable forecast errors contributes to more reliable proxies in estimating firm-level implied cost of capital. Moreover, firm-level predictability significantly impacts risk-averse investors who allocate funds across individual stocks and riskless cash (e.g., Kandel and Stambaugh, 1996). Lo and MacKinlay (1997) construct predictable and economically significant portfolios by applying maximally predictable individual stocks and bonds. Avramov and Chordia (2006) provide evidence that individual stocks are predictable based on macro variables, which substantially influences asset allocation in real-time. Thus, investigating firm-level predictability is attractive. However, skepticism about firm-level predictability exists due to concerns relating to the aggregate market's weak prediction evidence (Goyal and Welch, 2008).

Our paper investigates stock-level predictability and contributes to three strands of the literature. First, we test the forecasting performance of macroeconomic and technical indicators at the firm level based on the principal component analysis (PCA). Following NRTZ, we extract three principal components from the fourteen macroeconomic variables (PC-MACRO), one principal component from the fourteen firm-level technical indicators (PC-TECH), and four principal components from all the twenty-eight predictors (PC-ALL). We find strong individual stock return predictability from both fundamental indicators and technical variables, whereas NRTZ (2014) show that technical indicators generate higher predictive power than the macroeconomic variables in the market-level prediction.

The arbitrage pricing theory (APT) asserts that a firm's expected return is explained by the systematic risk in a factor model. When the time variation of systematic risk is driven by the economic environment, macroeconomic variables could exhibit some predictive power for individual stock returns. Empirically, Robichek and Cohn (1974) find that macroeconomic variables play an essential role in measuring the systematic risk of individual securities. Chen, Roll, and Ross (1986) show that macroeconomic variables systematically affect common stock returns. Contrary to macroeconomic variables, technical trading rules have been found relevant to the idiosyncratic risk (Arena, Haggard, and Yan, 2018; McLean, 2010). Moreover, when the stock price is noisy, the estimation of fundamental value is imprecise. Brown and Jennings (1989) argue that technical analysis helps market participants dealing with the noise instead of being a signal. Other studies examine the technical analysis in different contexts including information asymmetry (Grundy and Kim, 2002), behavioral bias (Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999), and asset allocation (Zhu and Zhou, 2010).

As aggregate macroeconomic variables and firm-level technical indicators have different influences on different sources of individual stock returns, using both information sets in the forecasts could generate more reliable firm-level predictability. Gupta and Wilton (1987) find that combining multiple forecasts improves the quality of estimates by facing a wide variety of information. Rapach, Strauss, and Zhou (2010) evident that combination forecasts deliver significant gains on stock return predictability over time and are closely linked to the real economy. We use a parsimonious model that incorporates information from macroeconomic variables and technical indicators to improve the firm-level predictability. Campbell, Lettau, Malkiel, and Xu (2001) find that investors bear higher idiosyncratic risk by investing in individual stocks rather than the aggregate market. Stambaugh, Yu, and Yuan (2012) note that stocks with higher idiosyncratic risk are more susceptible to greater arbitrage risk and mispricing. Moreover, Peng and Xiong (2006) show that limits to investor attention mean that firm-specific information is more likely to be overlooked than market-wide information. Consequently, we are motivated to fill this gap by applying both these two sets of indicators to investigate their predictive ability in the firm-level stock return analysis.

Second, we consider the effect of limits to arbitrage on predictability by applying the three most documented proxies: firm size, liquidity, and volatility. We find macroeconomic variables display a stronger predictive power in forecasting the returns of low arbitrage constraint firms, i.e., those with large size, high liquidity, and low return volatility. However, the PC-TECH model shows a stronger power in estimating the equity risk premium for the high limits to arbitrage firms, i.e., small, illiquid, and volatile firms. The results in the PC-ALL model confirm the complementary roles. The first principal component of the PC-ALL model behaves almost the same as the principal component in the PC-TECH model. However, the remaining three principal components show similar results to the three principal components in the PC-MACRO model.

Shleifer and Vishny (1997) suggest that limited and costly arbitrage opportunities drive stock prices far away from their fundamental values. The inefficient arbitrage of stock returns creates predictability opportunities. Lam and Wei (2011) find that there is a significant positive relationship between limits to arbitrage and the asset growth anomaly. Li and Zhang (2010) indicate higher limits to arbitrage firms earn higher expected returns by employing the q-theory. Moreover, macroeconomic variables and technical variables show different abilities in capturing various predictive information patterns. A sizable literature shows that large size, high liquidity, and low volatility firms are more sensitive to the change of macroeconomic conditions and are, therefore, more susceptible to changes in macroeconomic variables[2]. In contrast, technical analysis is widely applied for assessing stocks with less efficiency, and the prediction is mainly based on past price changes and perhaps other past statistics decisions[3]. Our results are highly consistent with the above-related areas of theoretical and empirical studies. We find a large proportion of stocks can be predicted by macroeconomic variables and technical indicators. We find evidence that such predictability may not be attributed to arbitrage opportunities. Lesmond, Schill, and Zhou (2004) find more predictability on relative illiquid securities; their costs are also substantial, making the arbitrage opportunity weaken.

Third, we assess the variation of individual stock return predictability over the business cycle and test whether the influence of limits to arbitrage changes through time. The overall results show that both macroeconomic and technical predictors display good predictive ability across the whole business cycle. Besides, macroeconomic variables

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[2] Chan, Chen, and Hsien (1985) find macroeconomic variables can explain the size effect. Chan and Chen (1991) indicate that large firms are more effective in dealing with market economic information than smaller firms are. Hu, Chen, Shao, and Wang (2019) find small stocks significantly outperform large stocks in the Chinese stock market. Chen and Mahajan (2010) find a positive relationship between macroeconomic factors and the firm's liquidity.

[3] De Long, Shleifer, Summers, and Waldmann (1990) show that in the presence of limits to arbitrage, noise traders with irrational sentiments make trading decisions based on current trading price rather than rational analysis of fundamental information of stocks, which drives the stock price far away from its instinct value.

perform comparatively better in recessions whereas technical indicators perform similarly across the economic states. NRTZ (2014) find that the macroeconomic variables and technical indicators display opposite roles in forecasting aggregate equity risk premium over the business cycle. That is, macroeconomic variables are more sensitive to the typical rise of equity premiums near cyclical throughs. In contrast, technical indicators can better capture the decline pattern of stock returns near business-cycle peaks. In this paper, we consider the role of limits to arbitrage during the business cycle, we find in recessions macroeconomic variables can better predict low arbitrage constraint firms. Technical indicators can explain variations of stock returns for high limits to arbitrage firms across the business cycle and even better in recessions.

The predictive power of various predictors is not constant but changes through time (Pesaran and Timmermann, 1995). Fama and French (1989) find that the default spread and the dividend yield display different roles in tracking expected returns across the business cycle. Thus, we motivate to ascertain how the macroeconomic variables and technical indicators perform in forecasting the risk premium for individual stocks with various limits of arbitrage over the business cycle. Our empirical results show that both macroeconomic and technical variables perform well over time, while technical predictors have stronger predictive power during the recession. For firms with different extent of limits to arbitrage, macroeconomic variables, and technical predictors display contrary but complementary predictive roles across the business cycle.

The remainder of this paper proceeds as follows. Section 2 presents the data and method. Empirical results are discussed in Section 3. Finally, Section 4 concludes.

2.2. Brief Review of the Literature

Regarding stock returns predictability, mounting empirical finance research evident that macroeconomic variables and technical indicators are the two prominent candidate predictors. Theoretically, macroeconomic variables that track economic activities should have the ability to predict stock price movement. Cochrane (2011) argues that this predictive ability is compensation of aggregate risk and consistent with rational asset pricing. Muth (1961) proposes the rational expectations hypothesis (REH), which plays a critical role in macroeconomic analysis. The relative theoretical work on technical analysis is generally based on the information inefficient and corresponding performance differences of investors. Treynor and Ferguson (1985) demonstrate that technical analysis helps assess other valuable information that is not fully revealed in past prices. Brown and Jennings (1989) claim that past prices enable investors to learn about the private price signals. Hong and Stein (1999) find that investors underreact to the news at the start of a trend but subsequently overreact, which leads price further deviate from its fundamental.

The utilization of macroeconomic variables in empirical analysis can be exploded since the 1920s by Dow, who explores the prediction ability of dividend ratios. After that, Fama and French (1988) and Campbell and Shiller (1988a) evident a positive relationship between dividend ratio and expected stock returns. Subsequent studies on dividend yield find a similar conclusion (Lewellen, 2004; Campbell and Yogo, 2006). Substantial papers find that other macroeconomic variables, including book-to-market value (Kothari and Shanken, 1997; Pontiff and Schall, 1998; Lewellen, 1999), dividend payout ratio (Campbell and Shiller, 1988), earnings (Lamont, 1998), inflation (Fama and Schwert, 1997; Pearce, and Roley, 1988), interest rate (Ang and Bekaert, 2002; Yi, Ma, Huang, Zhang, 2019) also evident in playing an important and significant role in forecasting stock returns.

Researchers who use technical indicators to forecast future returns believe the past price and volume patterns can identify price trends and persistency. Since the 1700s, speculator Munehisa Homma start to utilize techniques to amass wealth in the rice market of Japan, and this technique is evolved into the stock market and is known as candlestick patterns (Nison, 1991). In the 1800s, Charles H. Dow proposes the Dow Theory, a technical analysis based on stock price movement. A growing empirical literature supports technical predictors and finds their predictive ability is as good as those well-documented macroeconomic variables (Goh, Jiang, Tu, and Zhou, 2012; Neely, Rapach, Tu, and Zhou, 2014). Some researchers believe that the information detected by technical analysis exceeds the information already included in the current price (Neftci and Policano, 1984; Neftci, 1991; Brock, Lakonishok, and LeBaron, 1992; Neely, Weller and Dittmar, 1997; Lo, Mamaysky, and Wang, 2000). Exiting popular empirical technical analysis studies can be sorted into three trend-following techniques: moving average (Brock, Lakonishok, and LeBaron, 1992; LeBaron, 1999, and LeBaron, 2002), momentum (Ahn, Conrad, and Dittmar, 2003; Asness, Moskowiz, and Pedersen, 2013) and the trading volume-based rules (Grundy and McNichols, 1989; Blume, Easley, and O'Hara,1994).

Moreover, many studies reveal that macroeconomic variables and technical indicators have different predictive performances for size, liquidity and volatility sorted individual firms. Chan, Chen, and Hsien (1985) find that macroeconomic variables can explain the size effect well, while Chan and Chen (1991) indicate that large firms are more effective in dealing with market economic information than smaller firms. Moreover, Chen and Mahajan (2010) find a positive relationship between macroeconomic factors and corporate liquidity. For the technical analysis, Kavajecz and Odders (2004) claim that technical analysis provides a convenient way to locate liquidity on the book. Marshall, Qian, and Young (2009) show that technical analysis is more profitable for smaller, less liquid stocks.

The prediction pattern of macroeconomic variables and technical indicators is pervasive across markets, such as bonds, foreign exchange, sovereign debt, and houses prices. Numerous studies evident that macroeconomic variables can predict the bond risk premia on U.S. government bonds (Fama and Bliss, 1987; Keim and Stambaugh, 1986; Fama and French, 1989; Campbell and Shiller, 1991), while Goh, Jiang, Tu, and Zhou (2012) apply technical indicators can significantly forecast bond risk premium. Beltratti and Morana (2010) find a significant correlation between house prices and macroeconomic variables. Gourinchas and Rey (2007) show that high sovereign or foreign debt levels signal low returns, not higher government or trade surpluses.

Other markets also show significant predictability by utilizing macroeconomic variables and technical indicators. Chan, Hamao, and Lakonishok's (1991) study reveal a significant relationship between some selected macroeconomic variables and expected returns in the Japanese market. A negative relationship was found between inflation and stock index by the study of Roll and Geske (1983) and Chen, Rall, and Rose (1986) in the Tokyo stock exchange (TSE). For the technical analysis, Asprem (1989) evident that macroeconomic variables are also evident to provide predictive information in ten European countries. Coutts and Cheng (2000) examine the Hang Seng index by trading range break-out rule. Parisi and Vasquez (2000) examine the technical trading rules in Chilean indices.

2.3. Data and Method

2.3.1. Data

The sample in our article is all common stocks traded on the NYSE, AMEX, and NASDAQ exchanges with available monthly stock return data retrieved from the Center for Research in Security Press (CRSP) database. We retain all the firms with monthly observations for more than 10 years to ensure sufficient data in each regression. After excluding delisted stocks and the observations with monthly returns that are less than −100%, 9699 firms remain. For a full comparison with the market-level results, we employ the same two sets of predictors in the NRTZ's (2014) paper that start from December 1950 and extend to December 2018 in our sample. In contrast to the NRTZ (2014), we use the firm-level technical indicators constructed from the stock-level information. Our sample has the same start date as NRTZ (2014) as it is limited by the data availability of market volume in constructing technical indicators. The end date of our database is based on the latest information on the macroeconomic variables on Amit Goyal's website4 that are updated until December 2018. Besides, we collect the risk-free rate from Goyal's website with the same data range as the predictors.

2.3.2. Method

2.3.2.1. Principal Component Predictive Regression

We apply the principal component predictive regression in detecting the predictability of individual stocks as follows:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} + \varepsilon_{t+1}, \tag{2.1}$$

where y_{t+1} is the individual firm log excess return for the firm-level forecast or the S&P 500 log excess return for the market level estimation; $\hat{F}_{n,t}^{P}$ represents the *n*th principal component which incorporates information from the documented 14 fundamental variables (P = MACRO), 14 firm-level technical predictors[4] (P = TECH), or all the 28 predictors together (P = ALL). To compare our firm-level findings with NRTZ's (2014) market-level predictability results, we follow NRTZ (2014) to select the number of principal components N, where $N = 3$, $N = 1$, and $N = 4$ for the PC-MACRO, PC-TECH, and PC-ALL models, respectively. The critical value applied in our in-sample regression is based on the heteroscedasticity-consistent *t*-statistics by applying the Newey-West test under the hypothesis of $H_0\colon \beta_n = 0$ against $H_A\colon \beta_n \neq 0$. First, we group each stock coefficient into four groups: positive and significant (PS), positive and insignificant (PI), negative and significant (NS), and negative and insignificant (NI). We use the 10% statistical significance level. We assess whether the proportion in each group is statistically different from the random based on the critical p-value from a wild bootstrap procedure.

[4] Please see Appendix 1.1 for the construction details of the 14 firm-level technical indicators.

First, we create a bootstrapped predictor ($\hat{F}_t^B$) by randomly selecting observations with replacement from the original time-series predictors. The bootstrapped predictor has the same sample size and qualitatively similar characteristics to the original time series. Second, we use the bootstrapped predictor to forecast the individual stock excess return. We repeat this regression across all stocks. Third, based on the regression coefficient result in step 2, we calculate the proportion of positive and significant coefficients. Fourth, we repeat the process from step 1 to step 3 for 500 times. This will allow us to have the distribution of the positive and significant proportions of the bootstrapped predictor to calculate the p-value of the proportion of positive and significant results for each of the predictors.

Principal components analysis (PCA) is a mostly used tool in financial studies for parsimoniously incorporating information from a large group of predictors in the predictive regression (e.g., Zhu, 2014; Ludvigson and Ng, 2007). It supplies researchers with a low-dimensional data analysis. The primary principal components load the critical information from the entire set of predictors, thereby filters out much of the noise and prevent the overfitting problem by simulating using a large number of individual predictors. To assess how all the individual macroeconomic variables and technical indicators contribute to each principal component's predictability in equation (2.1), we apply the loading test. For each stock, we first get the principal score for all the macroeconomic variables and technical indicators on the principal component extracted in the principal component analysis in equation (2.1). Second, based on the principal scores for all firms, we calculate the average score and the positive proportion of the principal scores for each macroeconomic variable and technical indicator.

We examine the firm-level predictability based on macroeconomic and technical indicators by applying the conventional univariate predictive regression as follow:

$$y_{t+1} = \alpha_i + \beta_i x_{j,t} + \varepsilon_{j,t+1}, \tag{2.2}$$

where y_{t+1} is the individual firm log excess return for the firm-level forecast, or the S&P 500 log excess return for the market level estimation; $x_{j,t}$ represents the *j*th predictor from the documented 14 macroeconomic variables or 14 technical predictors.

The predictability results are categorized based on the ranking of the three popular arbitrage proxies: illiquidity, volatility, and size. First, the monthly volatility of each stock is computed by the standard deviation of its daily return. Second, the firm size is its monthly capitalization. Last, the firm’s illiquidity index is Amihud's (2002) illiquidity measure calculated as follows:

$$ILLIQ_t = 10^6 \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_t|}{DVOL_t}, \tag{2.3}$$

where R_t is the daily return of each stock in month *t*; $DVOL_t$ is the dollar volume, which equals daily price times daily trading volume, and D_t is the number of trading days in month *t*. This illiquidity index measures the changes in absolute returns for a given trading volume. The monthly illiquidity index of each firm is averaged from its daily illiquidity values in month *t*.

We further examine the predictability in different economic states by applying the following regression with recession and expansion dummy variables:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^{P} * DEXP_t + \varepsilon_{t+1}, \tag{2.4}$$

where $DREC_t$ ($DEXP_t$) represents the recession (expansion) dummy variable. We define these dummies in two ways. The first is based on the business cycle definitions in the National Bureau of Economic Research (NBER)[5]: $DREC_t$ equals one if the economy is classified as the recession by NBER, and zero otherwise. The second alternative is based on data from the Chicago Fed's National Activity Index (CFNAI)[6] index. When the index's three-month moving average (CFNAI-MA3) is less than -0.7, $DREC_t$ is equal to 1, and zero otherwise. $DEXP_t$ is simply one minus $DREC_t$ in both cases.

2.3.2.2. Prediction Differential between Limits to Arbitrage Firms

To measure the predictability difference between the highest and lowest limits to arbitrage firms, we retain all the firms with positive and significant estimated coefficients and apply the following linear regression:

$$D_{ps} = a_0 + a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4 D_4 + \varepsilon, \tag{2.5}$$

where D_{PS} is the dummy variable that takes a value of one for the firms with positive and

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[5] The data are available at http://www.nber.org/cycles/cyclesmain.html.
[6] The data are available at https://www.chicagofed.org/publications/cfnai/index.

significant estimated coefficients and zeroes otherwise. D_g (g = 1, 2, 3, 4) is the dummy variable that equals one for firms in the four different limits of arbitrage ranking groups and zeroes otherwise. We have five groups for each proxy (size, liquidity, and volatility) of limits of arbitrage. But we only include four dummy variables in the right-hand side of equation (2.5) to test the prediction difference between the lowest and highest limits to arbitrage firms. For example, D_1 (D_2, D_3, D_4) equals one for firms in the highest (second, third, fourth) limits of arbitrage level, and zero otherwise. The *t*-statistics of a_1 indicates whether the return predictability significantly differs between firms with the highest and lowest limits of arbitrage.

2.3.2.4. Profit-Making Strategy

We compute the profitability of the strategy based on the predictive power of the aggregate macroeconomic variable and firm-level technical indicator. First, at the end of each month, we regress the stock return and predictive variables as per equation (2.1) and compute the forecasted stock return for the following month based on past 120-month observations. Second, we rank all the securities into ten portfolios based on their forecasted returns. Firms in the top (bottom) decile portfolio that have the highest estimated returns are called "predicted winners" ("predicted losers"). Third, we buy the predicted winner portfolio and sell the predicted loser portfolio. We holding this position for one month and rebalance the strategy based on the process in the first two steps. After obtaining the monthly return of the strategy, we calculate the risk-adjusted returns by the four-factor Carhart model.

2.4. Empirical Results

2.4.1. Firm-Level Predictability Evidence

Table 2.1 contains both the market-level and firm-level predictive regression results based on the principal components analysis. The market-level estimated coefficients and the R^2-statistics in the second and third columns in Table 1 are similar to NRTZ despite our sample including a more recent period. The results indicate that the aggregate market return can be positively predicted by both macroeconomic and technical predictors.

To illustrate the firm-level results, we group the estimated coefficients, associated with each of the principal components and significant at the 10% level or better, into the positive (PS) and negative (NS) proportions in the fourth and fifth columns, respectively. The sixth column shows the differences between PS and NS and their *t*-statistics. For nine out of ten principal components (including the average proportions in the last row of Panel A and the fifth row of Panel C), the PS proportions are significantly higher than the NS proportions by a magnitude of between 3.70% and 19.15%. These firm-level results show that the predictability of macroeconomic variables and technical indicators is evident at the firm-level, especially for the second principal components $\hat{F}_{AVG}^{MACRO}$(21.33%) in Panel A and the fourth principal component $\hat{F}_{AVG}^{ALL}$ (14.54%) in Panel C. Moreover, we find most of the PS proportions predicted by the eight principal components in the fourth column are significant at the 1% level based on the one-sided wild bootstrap procedure.

The last column in Table 2.1 shows the firm-level average R^2 for the three principal component regression models. The average R^2 is 2.29% in Panel A for the model with macroeconomic principal components (PC-MACRO) and is 2.75% in Panel C for the model with both macroeconomic and technical principal components (PC-ALL), and both of these are higher than the R^2 for the market-level regressions. The average R^2 for the model with a technical principal component (PC-TECH) is 0.62% which is slightly lower than the market-level result but is above the 0.5% threshold.[7] Besides, we notice that the sum of the R^2 statistics for PC-MACRO (2.29%) and PC-TECH (0.62%) models roughly equals the R^2 for the PC-ALL (2.75%) model, which is consistent with NRTZ's (2014) finding at the market-level. They claim that the macroeconomic variables and technical predictors essentially contain complementary predictive information. More firm-level prediction evidence will be discussed in the following cross-sectional analysis.

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[7] Campbell and Thompson (2008) illustrate that a monthly R^2-statistic that is close to 0.5% represents an economically significant degree of equity risk premium predictability.

Table 2.1. Firm-level principal component analysis

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Market level				Firm-level		
P.C.	Slope coefficient	R^2(%)	PS(%)	NS(%)	PS(%) - NS(%)	R^2(%)	$ADJR^2$(%)
			Panel A: Macroeconomic variables				
$\hat{F}_1^{MACRO}$	0.04 [0.45]	1.19	8.32***	2.38	5.94 [4.25]***	2.29	0.81
$\hat{F}_2^{MACRO}$	0.07 [0.60]		21.33***	2.18	19.15 [14.20]***		
$\hat{F}_3^{MACRO}$	0.32 [2.50]***		12.30***	4.20	8.10 [5.89]***		
$\hat{F}_{AVG}^{MACRO}$			13.98	2.92	11.06 [8.05]***		
			Panel B: Technical variables				
$\hat{F}_1^{TECH}$	0.12 [2.05]**	0.78	7.78***	4.08	3.70 [2.66]***	0.62	0.08
			Panel C: All predictors				
$\hat{F}_1^{ALL}$	0.11 [1.91]*	1.96	8.98***	3.34	5.64 [4.05]***	2.75	0.62
$\hat{F}_2^{ALL}$	0.08 [0.88]		5.89**	3.66	2.23 [1.59]		
$\hat{F}_3^{ALL}$	0.17 [1.43]		11.07***	3.48	7.59 [5.49]***		
$\hat{F}_4^{ALL}$	0.26 [2.36]**		14.54***	4.11	10.43 [7.62]***		
$\hat{F}_{AVG}^{ALL}$			10.12	3.65	6.47 [4.67]***		
					$R_{ALL}^2 - R_{MACRO}^2$	0.46 [22.93]***	-0.18 [-8.71]***
					$R_{ALL}^2 - R_{TECH}^2$	2.13 [87.60]***	0.54 [24.10]***

This table shows principal component analysis (PCA) results at the market and firm-level based on the following regression:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} + \varepsilon_{t+1},$$

where y_{t+1} represents the market-level or individual firm level's natural logarithm of equity risk premium respectively. $\hat{F}_{n,t}^{P}$ is the *n*th principal component extracted from the documented 14 macroeconomic variables ($P = MACRO$), 14 technical predictors ($P = TECH$), or all the 28 predictors together ($P = ALL$). $N = 3$ ($N = 1$, $N = 4$) for the PC-MACRO (PC-TECH, PC-ALL) model in Panel A (B, C). We report collected market-level principal component prediction results from Neely et al.'s paper in the second and third columns by extending the data to December 2018. We report the positive and significant (PS), and negative and significant (NS) proportions of the estimated coefficients for each of these principal components in the fourth and fifth columns and the PS-NS proportion difference in the sixth column. We report the average R^2 and the average adjusted-R^2 in the last two columns. We calculate the difference in average R^2 and average adjusted R^2 between the PC-ALL model and PC-MACRO (PC-TECH) models in the last two rows of panel C. *t*-statistics are in brackets. ***, **, and * in column (4) indicates significance at the 10%, 5%, and 1% levels, respectively, according one-sided (upper-tail) wild bootstrapped p-values; ***, **, and * in the rest column indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table A 1.1 shows that the conventional bivariate predictive regression results are robust to the principal component predictive analysis (PCA) in Table 2.1. All the macroeconomic variables and most of the 14 technical variables exhibit significantly predictive power in forecasting individual firm returns. Macroeconomic variables: LTR, DMS, DY exhibit impressively predictive ability among all the predictors in the univariate predictive regression. Besides, Appendix Table A 1.2 illustrates that our results are robust to the same investment period of NRTZ (2014) that spans from December 1950 to December 2011. All the principal components show significant predictive power at the firm-level predictability. Besides, the findings on R^2- statistics are similar to Table 2.1, which further confirms the complementary role of macroeconomic and technical predictors displayed in predicting individual stock returns.

In Table 2.2 it is evident that our firm-level predictability contains meaningful economic information by applying the profit-making strategy. Panel A shows statistically significant average monthly returns of over 0.8% by holding the "predicted winner minus predicted loser" portfolios constructed based on the individual stock returns forecasted by all the three sets of principal components. Besides, the abnormal returns from the four-factor Carhart model in Panel B are positive and statistically significant. This suggests the four-factor model cannot fully explain the returns provided by the profit-making strategy. This evidence shows the forecasting power of the macroeconomic variables and technical indicators is robust and economically significant at the firm-level predictability.

Table 2.2. Profit-making strategy

(1)	(2)	(3)	(4)
	PC_MACRO	PC_TECH	PC_ALL
Panel A: Profit-making strategy returns			
Winner	-0.19% [-0.85]	-0.11% [-0.51]	-0.18% [-0.80]
Loser	-1.04% [-3.60]***	-0.95% [-3.24]***	-0.98% [-3.46]
WML	0.84% [5.35]***	0.84% [5.18]***	0.80% [6.04]***
Panel B: Risk-adjusted returns			
CH4 Alpha	0.62% [5.45]***	0.52% [4.96]***	0.53% [5.96]***
MKT	0.0235 [0.89]	-0.0087 [-0.35]	-0.0287 [-1.38]
SMB	-0.3156 [-8.33]***	-0.3670 [-10.37]***	-0.1926 [-6.42]***
HML	-0.3767 [-9.19]***	-0.2248 [-5.87]***	-0.1978 [-6.09]***
MOM	0.4215 [23.11]***	0.4830 [28.35]***	0.4050 [28.03]***

This table reports the monthly returns for the portfolios formed based on the profit-making strategy. At the end of each month, we rank all the stock into ten portfolios based on the estimated returns in the next month, calculated by the 120-month rolling regression of equation (1). Firms in the top (bottom) decile portfolio that have the highest estimated returns are called “winners” (“losers”). We buy the winner portfolio and sell the loser portfolio, holding this position for one month. After getting the monthly average returns, we calculate the risk-adjusted returns by the Carhart four-factor model. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

2.4.2. Cross-Sectional Predictability

The limits to arbitrage hypothesis suggest that firms with higher limits to arbitrage can earn larger risk-adjusted returns than their low limits to arbitrage counterparts (e.g., Whited and Wu, 2006; Li and Zhang, 2010). Thus, to investigate the influence of limits to arbitrage in predicting individual stock returns, we consider three primary aspects of limits of arbitrage in this section: the arbitrage risk (measured by volatility), transaction costs (measured by Amihud (2002) illiquidity), and the investment friction (measured by firm size). We keep all the positive and significant (PS) coefficients from each PCA predictive model and place them into five groups based on each firm's ranking of firm size, Amihud illiquidity, or volatility.

Tables 2.3 contains the size-sorted principal component predictive regression results. Macroeconomic variables in Panel A show stronger predictive power for the large firms while technical predictors in Panel B display better forecasting power for small firms. Panel A also shows that the PS proportions for the PC-MACRO model increase with the firm size. For example, 6.70% (20.01%, 9.95%) of small firms can be predicted by the first (second, third) principal component of macroeconomic variables. This proportion increases to 8.39% (21.75%, 15.38%) of large firms. However, Panel B displays a monotonically declining trend in the prediction proportion of the PC-TECH model with the PS proportion falling from 9.03% for small firms to 5.18% for large firms.

Furthermore, the results of the PC-All model in Panel C provide complementary evidence of macroeconomic variables and technical variables in forecasting the size-sorted individual firms. We find that the first two principal components ($\hat{F}_1^{ALL}$, $\hat{F}_2^{ALL}$) tend to predict smaller firms, and the result of the third principal component suggests a higher predictive capacity in forecasting the larger firms. Besides, we notice that the increasing trend and the magnitude of the predictive proportions of the first principal component ($\hat{F}_1^{ALL}$) for the PC-ALL model in Panel C are similar to that of the principal component ($\hat{F}_1^{TECH}$) of the PC-TECH model in Panel B. However, the third principal component ($\hat{F}_3^{ALL}$) of the PC-ALL model in Panel C perform more similar to the third principal component ($\hat{F}_3^{MACRO}$) of the PC-MACRO model in Panel A.

NRTZ (2014) shows that $\hat{F}_1^{ALL}$ behaves very similar to $\hat{F}_1^{TECH}$ as the 14 technical predictors load nearly uniformly on the first principal component of the PC-ALL model while the 14 macroeconomic variables load more heavily on the other three principal components extracted from the entire set of predictors. They suggest this is one of the evidences for macroeconomic and technical predictors in providing complementary predictive information to equity return prediction. We provide consistent evidence by applying the loading test at the firm-level prediction, and the detailed results are reported in Table 2.6 at the end of this section. Besides, our findings on the R^2-statistics support another evidence of the complementary pattern proposed by NRTZ (2014) that the sum of the average R^2 of the PC-MACRO model and the PC-TECH model closely equals the average R^2 of the PC-ALL model for all five size-sorted firm groups. Additionally, 11 of the 12 average R^2-statistics are above the 0.5% threshold.

Table 2.3. Size-sorted principal component analysis

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Positive and Significant Proportion			
P.C.	S (Small)	2	3	4	L (Large)	S-L [t-stat]
			Panel A: Macroeconomic variables			
$\hat{F}_1^{MACRO}$	6.70	8.30	8.56	9.65	8.39	-1.69 [-1.90]*
$\hat{F}_2^{MACRO}$	20.01	22.32	20.31	22.27	21.75	-1.74 [-1.32]
$\hat{F}_3^{MACRO}$	9.95	11.86	12.42	11.90	15.38	-5.43 [-5.15]***
$\hat{F}_{AVG}^{MACRO}$	12.22	14.16	13.76	14.61	15.17	-2.95 [-1.71]*
R_{MACRO}^2	2.61	2.55	2.31	2.22	1.75	0.86 [11.24]***
			Panel B: Technical variables			
$\hat{F}_1^{TECH}$	9.03	9.64	8.51	6.57	5.18	3.85 [4.47]***
R_{TECH}^2	0.77	0.69	0.62	0.55	0.46	0.31 [9.44]***
			Panel C: All predictors			
$\hat{F}_1^{ALL}$	8.92	10.88	10.98	8.11	6.01	2.91 [3.17]***
$\hat{F}_2^{ALL}$	6.91	5.46	6.29	6.16	4.61	2.30 [3.04]***
$\hat{F}_3^{ALL}$	9.28	11.49	9.38	11.80	13.41	-4.13 [-4.10]***
$\hat{F}_4^{ALL}$	13.51	15.00	14.79	14.37	15.02	-1.51 [-1.33]
$\hat{F}_{AVG}^{ALL}$	9.66	10.71	10.36	10.11	9.76	-0.11 [-0.07]
R_{ALL}^2	3.34	3.00	2.74	2.61	2.05	1.29 [14.52]***

This table shows the size-sorted estimate coefficients based on the principal component predictive regression results of equation (2.1) (see Table 2.1 description for more details). All the positive and significant estimated coefficients are sorted into five groups based on the ranking of the firm's size, and we report the proportions for firms with the smallest size in the second column and the largest size in the sixth column. The proportion difference between the smallest and largest firms is shown in the last column and the corresponding *t*-statistics in brackets comes from the estimated coefficient α_1 in the following linear regression:

$$D_{PS} = a_0 + a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4 D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different size-sorted groups (exclude the largest size group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firm is sorted in the smallest size group, otherwise zero. The *t*-statistics for the difference in average R^2 between the smallest and largest firms are in brackets and calculated from the equation above by replacing the D_{PS} with the R^2 from equation (2.1). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Moreover, the results in Appendix 1.3 deliver the same information as Table 2.3 applying the date range from January 1951 to December 2011 and the market-level technical indicators. Two principal components (and the average) in Panel A of the PC-MACRO model show a significantly higher ability in predicting the large firms. However, the technical indicators of the PC-TECH model have stronger predictive power for smaller firms. Moreover, the four principal components show both roles of macroeconomic and technical predictors in Panel C, that the first principal components perform better in forecasting small firms, which is the same as the effect of technical indicators in Panel B. The remaining three principal components have higher positive and significant proportions for large firms, which is in line with the effect of macroeconomic predictors in Panel A.

The liquidity-sorted principal component predictive regression results in Table 2.4 exhibit a similar predictive pattern to the size-sorted findings in Table 2.3. Macroeconomic predictors can better estimate the equity risk premium for high liquidity firms, while technical variables show stronger ability in capturing the predictive information of illiquidity stocks. Panel A of Table 2.4 shows that 6.08% (20.72%, 10.15%) of the least liquid firms in the second column can be predicted by the first (second, third) principal component of the PC-MACRO model whereas 8.82% (20.73%, 14.13%) of the most liquid firms is predictable in column six. However, technical predictors in Panel B display contrary roles in predicting liquidity-sorted firms as they show significantly stronger forecasting power for lower liquidity firms. The prediction proportion is 9.79% in the second column for illiquidity firms, which is significantly higher than the 5.42% for liquidity firms in the sixth column.

In Panel C, the complementary prediction roles of macroeconomic and technical variables again show up in predicting liquidity-sorted firms. The first principal components ($\hat{F}_1^{ALL}$) reports identical predictive information in forecasting low liquidity firms as the technical component in Panel B. However, the third component ($\hat{F}_3^{ALL}$) in Panel C shows stronger predictive ability in forecasting high liquidity firms which is consistent with the macroeconomic components in Panel A. The R^2 statistic in the last row of each panel diminishes with the increase in liquidity. Furthermore, the sum of the R^2 in Panel A and Panel B for the PC-MACRO and PC-TECH models closely equals the R^2 in panel C for all five liquidity-sorted groups. This finding is highly consistent with the size-sorted results in Table 2.3 and further supports the complementary prediction evidence of macroeconomic variables and technical indicators in predicting liquidity-sorted individual stocks.

Table 2.4. Liquidity-sorted principal component analysis

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Positive and Significant Proportion			
P.C.	L (Low Liquidity)	2	3	4	H (High Liquidity)	L-H [t-stat]
			Panel A: Macroeconomic variables			
$\hat{F}_1^{MACRO}$	6.08	8.66	8.66	9.38	8.82	-2.74 [-3.08]***
$\hat{F}_2^{MACRO}$	20.72	21.51	20.73	22.94	20.73	-0.01 [-0.03]
$\hat{F}_3^{MACRO}$	10.15	11.66	11.86	13.66	14.13	-3.98 [-3.81]***
$\hat{F}_{AVG}^{MACRO}$	12.32	13.94	13.75	15.33	14.56	-2.24 [-1.30]
R_{MACRO}^2	2.47	2.51	2.38	2.31	1.77	0.70 [8.99]***
			Panel B: Technical variables			
$\hat{F}_1^{TECH}$	9.79	8.41	8.30	7.01	5.42	4.37 [5.10]***
R_{TECH}^2	0.72	0.70	0.60	0.58	0.48	0.24 [6.83]***
			Panel C: All predictors			
$\hat{F}_1^{ALL}$	10.15	10.01	9.75	9.12	5.88	4.27 [4.67]***
$\hat{F}_2^{ALL}$	5.82	6.34	6.50	5.57	5.21	0.61 [0.82]
$\hat{F}_3^{ALL}$	9.95	9.74	9.90	12.37	13.36	-3.41 [-3.42]***
$\hat{F}_4^{ALL}$	14.64	14.90	13.31	15.00	14.80	-0.16 [-0.18]
$\hat{F}_{AVG}^{ALL}$	10.14	10.25	9.87	10.52	9.81	0.33 [0.34]
R_{ALL}^2	3.03	3.05	2.81	2.71	2.13	0.90 [10.03]***

This table shows the liquidity-sorted estimate coefficients based on the principal component predictive regression results of equation (2.1) (see Table 2.1 description for more details). All the positive and significant estimate coefficients are sorted into five groups based on the ranking of the firm's liquidity, and we report the proportions for the firms with the most illiquidity in the second column and most liquidity in the sixth column. The proportion difference between most illiquidity and liquidity firms shows in the last column and the corresponding *t*-statistic in brackets comes from the estimated coefficient α_1 in following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different liquidity-sorted groups (exclude the highest liquidity group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the most illiquidity group, otherwise zero. The *t*-statistic of the difference in average R^2 between the highest illiquidity and liquidity firms is in brackets and calculated from the equation above by replacing the D_{PS} with the R^2 from equation (2.1). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The volatility-sorted proportion results in Table 2.5 provide consistent evidence for macroeconomic variables and technical indicators in forecasting individual firms with the various extent of limits of arbitrage. Macroeconomic variables show stronger predictive power for firms with low volatility (i.e., low limits to arbitrage), while technical indicators exhibit higher predictive ability in forecasting high volatility firms (i.e., high limits to arbitrage). The second principal component in the PC-MACRO model in Panel A displays the highest predictive proportions. Among all the three principal components in the PC-MACRO model in Panel A, the second and third principal components, $\hat{F}_2^{MARCO}$ and $\hat{F}_3^{MACRO}$, together with the average proportion for the three principal components, $\hat{F}_{AVG}^{MARCO}$, all generate significantly higher positive and significant proportions (9.42%, 6.49%, and 4.56% respectively) in forecasting the low volatility firms. However, Panel B shows that the magnitude of the positive and significant proportions in the PC-TECH model significantly reduces with the decrease of volatility from 8.51% to 5.77%.

The results in Panel C provide complementary evidence for macroeconomic and technical variables in forecasting volatility-sorted firms. The first principal component of the PC-ALL model in Panel C exhibits higher positive and significant proportions for low volatility firms, which is consistent with the predictive ability of technical indicators in Panel B. The other three principal components of the PC-ALL model provide similar predictive information with those of the PC-MACRO model in Panel A. We can see that the magnitude of the R^2 in the last row of each panel is significantly reduced by the increase of volatility at the end of each panel, the explanation power is higher for the more volatile firm. For each volatility group, the sum of the R^2 in the PC-MACRO model in Panel A and the PC-TECH model in Panel B roughly equals the R^2 in PC-ALL model in Panel C. Thus, the R^2 results support our hypothesis of the complementary roles of macroeconomic and technical factors in predicting volatility-sorted firms.

Taken together, the results reported in Table 2.3 to Table 2.5 suggest that the principal components extracted from macroeconomic variables and technical indicators capture opposite but complementary information in the cross-sectional predictability of individual stock returns. Besides, macroeconomic variables have stronger predictive power in forecasting low limits to arbitrage (i.e., large size, high liquidity, and low volatility) firms, while technical predictors exhibit higher predictive ability in predicting high limits to arbitrage (i.e., small size, low liquidity, and high volatility) firms.

Table 2.5. Volatility-sorted principal component analysis

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Positive and Significant Proportion			
P.C.	H (High Volatility)	2	3	4	L (Low Volatility)	H-L [t-stat]
			Panel A: Macroeconomic variables			
$\hat{F}_1^{MACRO}$	8.77	8.66	10.10	7.53	6.55	2.22 [2.51]**
$\hat{F}_2^{MACRO}$	16.35	18.04	22.53	23.97	25.77	-9.42 [-7.19]***
$\hat{F}_3^{MACRO}$	9.80	8.81	12.27	14.33	16.29	-6.49 [6.17]***
$\hat{F}_{AVG}^{MACRO}$	11.64	11.84	14.97	15.28	16.20	-4.56 [-2.65]***
R^2_{MACRO}	2.43	2.21	2.43	2.25	2.12	0.31 [4.06]***
			Panel B: Technical variables			
$\hat{F}_1^{TECH}$	8.51	8.97	8.30	7.37	5.77	2.74 [3.18]***
R^2_{TECH}	0.69	0.64	0.63	0.56	0.56	0.13 [3.95]***
			Panel C: All predictors			
$\hat{F}_1^{ALL}$	10.47	10.00	10.05	8.45	5.93	4.54 [4.95]***
$\hat{F}_2^{ALL}$	5.93	5.93	6.60	6.03	4.95	0.98 [1.30]
$\hat{F}_3^{ALL}$	9.13	10.62	11.29	12.22	12.11	-2.98 [-2.96]***
$\hat{F}_4^{ALL}$	10.99	11.91	15.62	16.91	17.27	-6.28 [-5.56]***
$\hat{F}_{AVG}^{ALL}$	9.13	9.62	10.89	10.90	10.07	-0.93 [-0.99]
R^2_{ALL}	3.08	2.79	2.89	2.55	2.47	0.61 [6.74]***

This table shows the volatility-sorted estimate coefficients based on the principal component predictive regression results of equation (2.1) (see Table 2.1 description for more details). All the positive and significant estimate coefficients are sorted into five groups based on the ranking of the firm's volatility, and we report the proportions for the firms with the most volatility in the second column and least volatility in the sixth column. The proportion difference between highest volatility and lowest volatility firms shows in the last column and the corresponding *t*-statistic in brackets comes from the estimated coefficient α_1 in the following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different volatility-sorted groups (exclude the lowest volatility group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the most volatile group, otherwise zero. The *t*-statistic of the difference in average R^2 between the highest volatility and lowest volatility firms is in brackets and calculated from the equation above by replacing the D_{PS} with the R^2 from equation (1). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2.6 reports the positive proportion and average value of the principal scores for all the individual variables loaded on the principal components. The results are consistent with the findings on NRTZ's (2014) paper and provides significant complementary evidence for macroeconomic and technical predictors in providing complementary predictive information to equity return prediction. Panel A of Table 2.6 shows that DP, DY, and BM load most heavily on the first principal component ($\hat{F}_1^{MACRO}$) extracted from the 14 macroeconomic variables. They have the highest average principal scores and positively load on the $\hat{F}_1^{MACRO}$ over 95% of the principal component predictive regressions. Technical indicators in Panel B of Table 2.6 have nearly equally positive proportions and the average values of the principal scores, which indicates that these 14 technical predictors contribute essentially the same to the predictability of the first principal component, $\hat{F}_1^{TECH}$.

In Panel C, the estimated loadings for the four principal components extracted from the entire set of predictors reflect the complementary roles for macroeconomic variables and technical indicators in predicting individual stock returns. The second and third columns in Panel C show that the 14 technical variables' loadings are nearly uniformly and much heavier than the macroeconomic variables on the first principal component ($\hat{F}_1^{ALL}$). In opposite, macroeconomic variables display a dominant role in loading on the third and fourth principal components ($\hat{F}_3^{ALL}$, $\hat{F}_4^{ALL}$), whereas the technical variables are much weaker.

Table 2.6. Loadings on principal components

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variable	PEC	ASCORE	Variable	PEC	ASCORE	Variable	PEC	ASCORE	Variable	PEC	ASCORE
				Panel A: PC-MACRO						Panel B: PC-TECH	
	$\hat{F}_1^{MACRO}$			$\hat{F}_2^{MACRO}$			$\hat{F}_3^{MACRO}$			$\hat{F}_1^{TECH}$	
DP	98.18	0.3729	DY	84.96	0.1304	DFY	75.86	0.0895	MOM_9	99.90	0.2493
DY	98.18	0.3704	INFL	84.96	0.1590	INFL	75.07	0.0871	MA_1_9	99.89	0.2653
BM	97.65	0.3311	TBL	83.95	0.1987	TBL	74.26	0.1186	MA_1_12	99.89	0.2798
DFY	92.57	0.2383	TMS	83.7	0.3282	BM	73.33	0.0749	MA_3_9	99.88	0.2684
RVOL	76.29	0.0762	DP	82.17	0.1221	LTR	65.34	0.1581	MA_3_12	99.88	0.2714
NTIS	75.89	0.0897	DE	77.95	0.2503	DP	65.23	0.0200	MA_2_12	99.87	0.2837
LTR	74.05	0.0157	DFR	75.23	0.0583	RVOL	62.07	0.0512	MOM_12	99.87	0.2130
EP	73.16	0.2034	BM	72.49	0.1175	LTY	61.64	0.1138	MA_2_9	99.86	0.2752
DE	57.12	0.0363	DFY	69.74	0.1944	DY	60.71	0.0165	VOL_1_9	98.39	0.2565
TMS	52.8	0.0307	RVOL	66.53	0.0767	NTIS	58.41	0.0765	VOL_1_12	98.36	0.2653
DFR	48.65	0.0132	LTR	56.2	0.0301	EP	57.93	0.0323	VOL_2_9	98.35	0.2672
TBL	33.34	-0.1095	NTIS	55.21	-0.006	TMS	54.12	0.0709	VOL_2_12	98.32	0.2695
LTY	29.36	-0.1549	LTY	46.11	0.0072	DE	51.98	0.0038	VOL_3_9	98.32	0.2633
INFL	27.88	-0.0989	EP	29.03	-0.0260	DFR	42.49	-0.0996	VOL_3_12	98.29	0.2604
						Panel C: PC-ALL					
	$\hat{F}_1^{ALL}$			$\hat{F}_2^{ALL}$			$\hat{F}_3^{ALL}$			$\hat{F}_4^{ALL}$	
MA_1_9	98.76	0.2272	BM	83.05	0.1998	BM	71.43	0.0909	BM	71.42	0.0645
MA_1_12	98.7	0.2414	DY	85.86	0.2433	DY	75.44	0.1007	INFL	79.99	0.1119
MA_2_9	98.69	0.2352	DP	85.84	0.2429	INFL	74.77	0.0747	DFY	77.39	0.1470
MA_3_9	98.67	0.2300	DFY	82.09	0.1647	TMS	74.47	0.1760	TBL	75.97	0.1120
MOM_9	98.67	0.2181	MA_1_9	78.94	0.0885	DP	73.71	0.0966	DY	72.48	0.0626
MOM_12	98.64	0.1909	MA_2_9	78.22	0.0912	DFY	72.86	0.1426	TMS	72.06	0.1608
MA_2_12	98.63	0.2444	MA_3_9	77.62	0.0867	DE	72.18	0.1564	DE	71.29	0.1294
MA_3_12	98.59	0.2347	MA_1_12	77.3	0.0878	TBL	70.01	0.1059	DP	70.43	0.0574
VOL_1_9	97.82	0.2347	MA_2_12	76.42	0.0882	DFR	65.88	0.0366	RVOL	64.21	0.0809
VOL_2_9	97.8	0.2443	MA_3_12	75.22	0.0814	RVOL	63.78	0.0673	LTR	59.21	0.0600
VOL_1_12	97.78	0.2448	MOM_9	71.53	0.0654	LTR	54.97	0.0151	DFR	58.77	0.0185

VOL_2_12	97.75	0.2490	VOL_1_9	70.63	0.0500	VOL_1_9	54.91	0.0225	NTIS	56.84	0.0346
VOL_3_9	97.73	0.2416	VOL_2_9	70.39	0.0512	NTIS	54.62	-0.0024	MOM_9	55.19	0.0128
VOL_3_12	97.7	0.2418	VOL_3_9	69.26	0.0478	VOL_2_9	54.31	0.0202	MOM_12	54.29	0.0115
TMS	65.57	0.0313	NTIS	69.13	0.0631	VOL_1_12	54.09	0.0180	MA_3_12	53.90	0.0096
TBL	60.16	0.0322	VOL_1_12	68.37	0.0465	MA_1_9	53.88	0.0158	MA_2_12	53.13	0.0094
DFR	58.77	0.0046	VOL_2_12	67.44	0.0454	VOL_3_9	53.88	0.0165	MA_3_9	52.46	0.0086
INFL	54.91	0.0245	VOL_3_12	66.44	0.0405	MA_2_9	53.54	0.0153	MA_1_12	52.22	0.0071
LTY	54.44	0.0150	RVOL	66.39	0.0594	VOL_2_12	53.41	0.0149	MA_2_9	51.83	0.0081
NTIS	49.28	0.0016	MOM_12	63.31	0.0415	MA_3_9	52.89	0.0118	LTY	51.18	0.0319
EP	48.75	-0.0205	EP	60.77	0.0828	VOL_3_12	52.71	0.0108	MA_1_9	50.73	0.0058
DE	46.82	0.0026	TMS	60.43	0.0601	MA_1_12	52.41	0.0115	VOL_1_9	45.57	-0.0065
BM	35.73	-0.0468	DE	60.09	0.0694	MA_2_12	51.65	0.0108	VOL_2_9	45.25	-0.0085
LTR	35.63	-0.0093	LTR	59.35	0.0086	MOM_9	51.26	0.0067	VOL_1_12	45.07	-0.0091
RVOL	35.37	-0.0244	DFR	57.08	0.0178	MA_3_12	51.01	0.0074	VOL_2_12	44.95	-0.0115
DY	34.74	-0.0463	TBL	45.32	-0.0157	MOM_12	49.91	0.0024	VOL_3_9	44.70	-0.0112
DP	33.31	-0.0509	INFL	42.01	-0.0385	LTY	46.94	-0.0020	VOL_3_12	44.58	-0.0142
DFY	28.13	-0.0524	LTY	40.76	-0.0603	EP	43.89	-0.0219	EP	38.42	-0.0198

This table reports the positive proportion and average value of the principal component scores for all the individual macroeconomic variables and technical indicators on all the principal components from the following firm-level regression:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} + \varepsilon_{t+1},$$

where y_{t+1} represents the individual firm level's log equity risk premium. $\hat{F}_{n,t}^{P}$ is the *n*th principal component extracted from the documented 14 macroeconomic variables ($P = MACRO$), 14 technical predictors ($P = TECH$), or all the 28 predictors together ($P = ALL$). $N = 3$ ($N = 1$, $N = 4$) for the PC-MACRO (PC-TECH, PC-ALL) model in Panel A (B, C). "PEC" column corresponds to the positive proportion for each variable to get the positive scores in all the regression and the "ASCORE" column represents the average principal component scores of each variable. We rank all the variables in descending order based on their positive proportion.

2.4.3. Predictability during Recessions and Expansions

The predictive regression results in the following section further provide insight into the performance of the macroeconomic and technical indicators at the firm-level predictability across different economic states.

The results in Table 2.7 report the overall predictability of individual stock returns across the business cycle. Columns two to five report the proportions of positive and significant (PS) coefficients and negative and significant (NS) coefficients under recession and expansion periods separately. Column six (seven) shows the proportion of differences between PS and NS and their *t*-statistics for the recession (expansion) period. Column eight reports the PS differences between recession and expansion periods.

Generally, the results in Panels A and B show that both macroeconomic and technical predictors well perform across the whole business cycle as shown in columns six and seven. In column eight, macroeconomic variables perform comparatively better in recession periods than in expansion periods while the performance of technical variables is not different between the two economic periods. The relatively better predictability of these combined variables in recession periods is also confirmed in Panel C where all the PS differences in column eight are statistically significant. Our results are consistent with Pesaran and Timmermann (1995) that more important gains are yielded during the volatile periods than the relatively calm time.

Table 2.7. Principal component analysis across business cycle

(1)	(2)	(3)	(4)	(5)	(6) [(2) - (3)]	(7) [(4) - (5)]	(8) [(2) - (4)]	(9)
	REC (β_n)		EXP (γ_n)		$PS^R - NS^R$	$PS^E - NS^E$	$PS^R - PS^E$	R^2(%)
P.C.	PS	NS	PS	NS	[t-stat]	[t-stat]	[t-stat]	
Panel A: Macroeconomic variables								
$\hat{F}_1^{MACRO}$	7.88	5.68	10.92	2.25	2.20 [1.58]	8.67 [6.25]***	-3.04 [-2.23]**	4.26
$\hat{F}_2^{MACRO}$	21.09	3.57	16.24	2.34	17.52 [13.04]***	13.90 [10.16]***	4.86 [3.75]***	
$\hat{F}_3^{MACRO}$	13.60	8.31	9.73	3.25	5.29 [3.90]***	6.48 [4.67]***	3.87 [2.86]***	
$\hat{F}_{AVG}^{MACRO}$	14.19	5.85	12.30	2.61	8.34 [9.48]***	9.69 [11.43]***	1.89 [2.45]***	
Panel B: Technical variables								
$\hat{F}_1^{TECH}$	6.94	4.55	7.20	4.48	2.39 [1.72]*	2.72 [1.96]**	-0.33 [-0.19]	1.29
Panel C: All predictors								
$\hat{F}_1^{ALL}$	10.80	11.69	7.55	4.99	-0.89 [-0.66]	2.56 [1.84]*	3.25 [2.37]**	5.84
$\hat{F}_2^{ALL}$	12.39	9.85	8.31	4.19	2.54 [1.88]*	4.12 [2.97]***	4.08 [3.07]***	
$\hat{F}_3^{ALL}$	17.16	9.03	9.78	3.88	8.13 [6.07]***	5.90 [4.25]***	7.38 [5.73]***	
$\hat{F}_4^{ALL}$	18.70	8.94	10.88	3.93	9.76 [7.32]***	6.95 [5.03]***	7.83 [5.90]***	
$\hat{F}_{AVG}^{ALL}$	14.76	9.88	9.13	4.25	4.88 [7.27]***	4.88 [7.04]***	5.63 [8.36]***	
							$R_{ALL}^2 - R_{MACRO}^2$	1.58 [29.03]***
							$R_{ALL}^2 - R_{TECH}^2$	4.55 [94.78]***

This table reports firm-level predictability results across the business cycle using the following equation:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^{P} * DEXP_t + \varepsilon_{t+1},$$

where y_{t+1} represents the market-level or individual firm level's log equity risk premium respectively. $\hat{F}_{n,t}^{P}$ is the *n*th principal component extracted from the documented 14 macroeconomic variables ($P = MACRO$), 14 technical predictors ($P = TECH$), or all the 28 predictors together ($P = ALL$). $DREC_t$ ($DEXP_t$) is the NBER recession (expansion) dummy variable equal to unity when month *t* is in recession (expansion) and zero otherwise, and $DEXP_t = 1 - DREC_t$. We report the positive and significant (PS), and negative and significant (NS) proportions of the estimated coefficients for each of these principal components. The average R^2 is in the last column. The *t*-statistic for the proportion difference or the R^2 difference is in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The R^2 for all the three models in the ninth column is larger than the R^2 in Table 1 after adding the recession and expansion of dummy variables into the equation (2.4). Moreover, it is again in line with the complementary behavior that the average R^2 for the PC-ALL model in panel C is 5.84%, which closely equals the sum of the average R^2 for the PC-MACRO model (4.26%) and the PC-TECH model (1.29%). We report the R^2 difference between the PC-ALL model and the PC-MACRO (PC-TECH) model at the bottom of Panel C. Two pairs of differences are both significant at a 1% level, which suggests that the macroeconomic variables and technical indicators capture different predictive information across the business cycle. Appendix 4 reports the results when recession and expansion periods are classified based on the CFNAI-MA3 index. The results are highly consistent with those in Table 2.7.

2.4.4. Cross-Sectional Predictability during Recessions and Expansions

We have shown that the previously documented predictability of macroeconomic and technical variables for market returns is also evident at the individual firm level, and their predictive abilities vary with the degree of limits of arbitrage in the cross-section and the macroeconomic conditions in the time series. In this section, we further investigate whether the cross-sectional predictability of individual stock returns changes under different economic states.

Table 2.8 represents the size-sorted principal component predictive regression results across the business cycle. To get a sense of how macroeconomic and technical indicators work for the size-sorted firms across the business cycle, we only report the positive and significant proportions of the largest and smallest size quintiles. Panel A suggests that macroeconomic variables do better in predicting large firms in recession than in expansion. However, the results in Panel B indicates that technical indicators predict small firms consistently better across the whole business cycle, and even better in the recession. The positive and significant predictive proportion of small firms substantially exceeds that of large firms during both recession and expansion periods by 8.14% and 4.06% respectively. Besides, the 3.48% difference between these two proportions is also statistically significant, indicating that technical variables have even stronger power in predicting smaller firms during the recession.

Turning to the results in Panel C, we show the regression results of the PC-ALL model, which parsimoniously incorporates information from both the macro and technical predictors. The complementary prediction role of macroeconomic variables and technical indicators again shows up in predicting the size-sorted individual firms across different economic states. The first principal component in Panel C exhibits a similar finding for technical predictors in Panel B that they provide stronger predictive information for small firms in recession. The results for the other three components in Panel C are consistent with those in Panel A that macroeconomic variables better forecast large firms in recession. Moreover, the proportion difference between the fourth and seventh columns accord with the above findings to further support the complementarity evidence. The difference between small and large firms' predictability is 2.15% significantly larger during recessions for the first principal component, $\hat{F}_1^{ALL}$, whereas that difference is -2.55% and -3.34% significantly smaller during recessions for the second and fourth principal components, $\hat{F}_2^{ALL}$ and $\hat{F}_4^{ALL}$, associated with the macroeconomic predictors. Smaller firms have significantly higher R^2 in the prediction regression than large firms in all three panels.

Table 2.8. Size-sorted PCA results across business cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession			Expansion			$(S-L)^R-(S-L)^E$
P.C.	S	L	$(S-L)^R$[t-stat]	S	L	$(S-L)^E$[t-stat]	[F-Stat]
			Panel A: Macroeconomic variables				
$\hat{F}_1^{MACRO}$	8.25	9.06	-0.81 [-0.94]	11.04	8.03	3.01 [3.00]***	-3.82 [8.27]***
$\hat{F}_2^{MACRO}$	18.21	22.22	-4.01 [-3.06]***	16.45	14.50	1.95 [1.65]*	-5.96 [12.32]***
$\hat{F}_3^{MACRO}$	13.10	15.90	-2.80 [-2.54]***	7.74	10.98	-3.24 [-3.40]***	0.44 [0.10]
$\hat{F}_{AVG}^{MACRO}$	13.19	15.73	-2.54 [-1.48]	11.74	11.17	0.57 [0.33]	-3.11
R^2_{MACRO}	4.41	3.85	0.56 [4.76]***				
			Panel B: Technical variables				
$\hat{F}_1^{TECH}$	11.40	3.26	8.14 [10.01]***	8.72	4.66	4.06 [4.89]***	3.48 [12.53]***
R^2_{TECH}	1.40	1.15	0.25 [4.20]***				
			Panel C: All predictors				
$\hat{F}_1^{ALL}$	13.26	9.89	3.37 [3.38]***	7.64	6.42	1.22 [1.43]	2.15 [2.72]***
$\hat{F}_2^{ALL}$	11.71	13.10	-1.39 [-1.31]	8.36	7.20	1.16 [1.31]	-2.55 [3.48]***
$\hat{F}_3^{ALL}$	14.96	17.92	-2.96 [-2.44]***	9.13	10.41	-1.28 [-1.34]	-1.68 [1.23]
$\hat{F}_4^{ALL}$	17.23	21.60	-4.37 [-3.48]***	11.09	12.12	-1.03 [-1.02]	-3.34 [4.69]***
$\hat{F}_{AVG}^{ALL}$	14.29	15.63	-1.34 [-0.83]	9.06	9.04	0.02 [0.01]	-1.36
R^2_{ALL}	6.14	4.58	1.56 [13.14]***				

This table shows the size-sorted principal component predictive regression results across the business cycle of equation (4) (see Table 5 description for more details). The *t*-statistic in brackets is for the proportion difference between the smallest (S) and largest (L) firms and calculated from α_1 in the following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different size-sorted groups (exclude the largest size group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the smallest size group, otherwise zero. Columns 2, 3, 5, and 6 show the positive and significant proportions of slope coefficients for the smallest and largest firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2.9 shows the principal component analysis results sorted by Amihud's (2002) illiquidity measure across the business cycle. We compare the positive proportions for the highest illiquidity firms and the lowest illiquidity firms during recessions and expansions, respectively. The principal components extracted from macroeconomic variables in Panel A exhibit consistently and significantly higher predictive ability for high liquidity firms in recession periods. The fourth column in Panel A shows that the positive and significant proportion for high liquidity firms is at least 2.79% higher than that for low liquidity firms, with an average difference at 3.03%. However, the results of technical indicators in Panel B show the prediction proportion for illiquidity firms in the second and fifth columns is significantly larger than for liquidity firms in both recession and expansion periods. The difference in low–high liquidity firms predictability confirms that both macroeconomic and technical indicators possess stronger predictive power in recession, as shown in column eight.

The results in Panel C reiterate the notion of the complementary roles of macroeconomic and technical indicators in forecasting liquidity-sorted firms, especially during the recession. The first principal component in Panel C displays the same role of technical indicators in Panel B that it does better in forecasting low liquidity firms during both recession and expansion. However, the other three principal components exhibit similar information of macroeconomic variables in Panel A that they perform better predictions of high liquidity firms during more volatile periods, i.e. recessions.

Table 2.9. Liquidity-sorted PCA results across business cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession			Expansion			$(L-H)^R-(L-H)^E$
P.C.	L	H	$(L-H)^R$[t-stat]	L	H	$(L-H)^E$[t-stat]	[F-Stat]
Panel A: Macroeconomic variables							
$\hat{F}_1^{MACRO}$	6.65	9.64	-2.99 [-3.45]***	10.62	9.13	1.49 [1.40]	-4.48 [10.90]***
$\hat{F}_2^{MACRO}$	17.99	20.78	-2.79 [-2.16]**	16.03	13.92	2.11 [1.75]*	-4.90 [8.32]***
$\hat{F}_3^{MACRO}$	11.80	15.11	-3.31 [-3.04]***	7.68	10.16	-2.48 [-2.65]***	-0.83 [0.35]
$\hat{F}_{AVG}^{MACRO}$	12.15	15.18	-3.03 [-1.76]*	11.44	11.07	0.37 [0.21]	3.40
R^2_{MACRO}	4.20	3.90	0.30 [2.46]***				
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	10.46	3.92	6.54 [8.06]***	8.71	4.80	3.91 [4.73]***	1.74 [5.21]***
R^2_{TECH}	1.37	1.20	0.17 [2.85]***				
Panel C: All predictors							
$\hat{F}_1^{ALL}$	11.86	10.11	1.75 [1.77]*	8.41	6.65	1.76 [2.08]**	-0.01 [0.00]
$\hat{F}_2^{ALL}$	11.04	13.20	-2.16 [-2.03]**	8.10	8.61	-0.51 [-0.57]	-1.65 [1.45]
$\hat{F}_3^{ALL}$	14.03	18.00	-3.97 [-3.31]***	9.80	10.57	-0.77 [-0.80]	-3.20 [4.62]***
$\hat{F}_4^{ALL}$	17.74	20.78	-3.04 [-2.46]***	11.66	11.60	0.06 [0.06]	-3.10 [4.15]***
$\hat{F}_{AVG}^{ALL}$	13.67	15.52	-1.86 [-1.16]	9.49	9.36	0.13 [0.08]	-1.98
R^2_{ALL}	6.13	4.85	1.28 [8.33]***				

This table shows the liquidity-sorted principal component predictive regression across the business cycle of equation (2.4) (see Table 2.5 description for more details). The *t*-statistic in brackets is for the proportion difference between the lowest (L) and highest (H) liquidity firms and calculated from α_1 in the following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different liquidity-sorted groups (exclude the highest liquidity group with $\mathrm{g} = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the most illiquidity group, otherwise zero. Columns 2, 3, 5, and 6 show the positive and significant proportions of slope coefficients for the lowest and highest liquidity firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2.10 presents the results of volatility-sorted principal component analysis results during recessions and expansions, respectively. The results for macroeconomic components in Panel A show mixed evidence on their predictability between high and low volatility firms and between recession and expansion periods. However, in line with the above size-sorted and liquidity-sorted findings, technical indicators in Panel B consistently show stronger predictive power in forecasting high limits to arbitrage (i.e., volatile) firms in both states of the economy. The results in Panel C suggests better predictability of macroeconomics-associated components for low volatility firms in recession. The R^2 in the last is higher for high volatility firms in all three panels. Moreover, the R^2 for the PC-ALL model closely equals the sum of the R^2 for the PC-MACRO and PC-TECH models.

Table 2.10. Volatility-sorted PCA results across business cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession			Expansion			$(H-L)^R-(H-L)^E$
P.C.	H	L	$(H-L)^R$[t-stat]	H	L	$(H-L)^E$[t-stat]	[F-Stat]
Panel A: Macroeconomic variables							
$\hat{F}_1^{MACRO}$	10.31	6.49	3.82 [4.42]***	11.09	8.51	2.58 [2.58]***	1.24 [0.87]
$\hat{F}_2^{MACRO}$	20.68	21.70	-1.02 [-0.78]	12.27	19.59	-7.32 [-6.19]***	6.30 [13.76]***
$\hat{F}_3^{MACRO}$	14.80	13.97	0.83 [0.76]	7.43	12.53	-5.10 [-5.37]***	-2.32 [18.26]***
$\hat{F}_{AVG}^{MACRO}$	15.26	14.05	1.21 [0.71]	10.26	13.54	-3.28 [-1.88]*	1.74
R^2_{MACRO}	4.42	4.06	0.36 [3.09]***				
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	8.87	5.00	3.87 [4.75]***	8.41	5.26	3.15 [3.80]***	0.72 [0.39]
R^2_{TECH}	1.34	1.16	0.18 [3.06]***				
Panel C: All predictors							
$\hat{F}_1^{ALL}$	11.19	10.21	0.98 [0.99]	8.15	7.37	0.78 [0.92]	0.20 [0.03]
$\hat{F}_2^{ALL}$	12.69	12.37	0.32 [0.30]	8.20	7.73	0.47 [0.53]	-0.15 [0.01]
$\hat{F}_3^{ALL}$	15.68	18.20	-2.52 [-2.08]**	9.74	9.54	0.20 [0.22]	-2.72 [3.27]***
$\hat{F}_4^{ALL}$	15.01	20.82	-5.81 [-4.65]***	9.18	12.37	-3.19 [-3.19]***	-2.62 [2.91]***
$\hat{F}_{AVG}^{ALL}$	13.64	15.40	-1.76 [-1.10]	8.82	9.25	-0.43 [-0.27]	-1.32
R^2_{ALL}	6.31	5.26	1.05 [6.91]***				

This table shows the volatility-sorted principal component analysis results across the business cycle by equation (2.4) (see Table 2.5 description for more details). The *t*-statistic in brackets is for the proportion difference between the highest (H) and lowest (L) volatility firms and calculated from α_1 in the following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different volatility-sorted groups (exclude the highest volatility group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the most volatile group, otherwise zero. Columns 2, 3, 5, and 6 show the positive and significant proportions of slope coefficients for the most and least volatile firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

2.5. Conclusions

We utilize both the well-documented macroeconomic variables and technical indicators to ascertain the less known firm-level predictability. We find both macroeconomic and technical indicators exhibit significant predictive ability for the individual stock monthly returns. However, they display the opposite but complementary predictive roles in forecasting the stock returns for different individual firms based on the extent of limits to arbitrage. Macroeconomic variables show stronger predictive power in forecasting the low arbitrage constraint (i.e., large, liquid, low volatility) firms, while technical variables catch more predictive information for the high limits to arbitrage (i.e., small, illiquid, volatile) firms. Moreover, the predictive regression results across the business cycle demonstrate that both macroeconomic and technical variables generate stable predictive information over time but even better in recession. Besides, macroeconomic and technical indicators have different abilities in processing information about various limits of arbitrage levels in individual firms under two economic states. Technical predictors consistently show significantly higher predictive ability on firms with high limits to arbitrage. However, macroeconomic variables show a higher predictive ability for firms with low limits to arbitrage in recession than in expansion.

NRTZ (2014) find that market-level stock returns can be well-predicted by aggregate macroeconomic variables and technical indicators. The analysis of individual stock returns predictability in this study provides new evidence about the financial market prediction at the stock level. The above results can be used by the firm managers who estimate the firm-level implied cost of capital and risk-averse investor who allocate funds across individual stocks and riskless cash. For example, investors can use technical indicators when selecting smaller, low-liquid, and high-volatile firms, whereas using macroeconomic variables when allocating funds across firms with large size, high liquidity, and low volatility. Our results indicate that technical indicators perform better in forecasting the high limits of arbitrage firms.

A large body of growing empirical studies reports the importance of predicting individual stock returns for various participators in the financial market. Macroeconomic variables and technical indicators are the most popular types of predictive variables. Comprehensively exploring the predictive performance of macroeconomic and technical indicators improves our understanding of how the two types of predictors work in estimating the risk premium of individual firms. The possible future works could be extended to assess the cost of capital (e.g., Mohanram and Gode, 2013), or to improve the investment asset allocation under the predictable individual risk premium, as in the work of Kandel and Stambaugh (1996).

CHAPTER THREE: Technical Indicators and Cross-Sectional Expected Returns

As found in the previous essay, individual stock returns can be well predicted by the 14 market-level macroeconomic variables and 14 firm-level technical indicators. In addition, they play different roles in predicting firms with various limits of arbitrage levels. What follows is to explore the relationship between individual technical indicators and cross-sectional stock returns, given the fact that technical indicators are well-applied in trading by top traders and investors. Besides, when information about stocks is uncertain, investors tend to rely more heavily on technical signals as fundamental signals can be imprecise. By adopting the smoothed OLS model, the explanatory ability of technical indicators for the cross-sectional expected stock returns is documented accordingly.

3.1. Introduction

Numerous empirical studies document evidence on the time-series aggregate market predictability based on technical indicators (e.g., Brock, Lakonishok, and LeBaron, 1992; Metghalchi, Marcucci, and Chang, 2012; Neely, Rapach, Tu, and Zhou, 2014). However, much less is known about how technical indicators explain the cross-sectional equity returns. We contribute to the literature by applying 14 well documented technical indicators to determine the cross-section of stock returns beyond the well-known determinants such as momentum, size, book-to-market ratio, operating profits, and investment.

Neely, Rapach, Tu, and Zhou (2014) summarize four types of informationally inefficient market leaded theoretical models to support the efficacy of technical analysis. Numerous studies document evidence that technical analysis involving past prices or other past data could predict time series stock returns (Lo, Mamaysky, and Wang, 2000; Yamamoto, 2012; Zeng, Marshall, Nguyen, and Visaltanachoti, 2021). Relative to times-series stock returns prediction, research on cross-section stock returns explanatory by technical indicators have received significantly less attention. However, Neely, Rapach, Tu, and Zhou (2014) find that technical indicators significantly forecast the sentiment-changes index, while Baker and Wurgler (2006, 2007) show that investor sentiment measures help explain the cross-section of U.S. equity returns. We thus shed light on the explanation ability of technical indicators on the cross-section of stock returns.

Our study contributes to previous literature in two ways: First, we contribute to the literature on technical analysis by providing an investigation of its application in a cross-sectional asset pricing setting. Technical rules involving past prices or other past data are widely used in a time series setting in stock markets. Brock, Lakonishok, and LeBaron (1992) find strong evidence regarding the profitability of technical indicators, while Lo, Mamaysky, and Wang (2000) demonstrate that technical analysis provides incremental information that is useful in the investment process. Others consider technical trading rules in other markets, such as currency markets (e.g., Bauer and Herz, 2005; Yamani, 2021) and bond markets (e.g., Montgomery, Raza, and Ulku, 2018). Zhu and Zhou (2009) provide theoretical motivation for the use of technical analysis. They claim that technical analysis is a valuable tool for understanding market uncertainty, which helps investors learn about predictability and thus adds value to asset allocation. However, compared with times-series stock returns analysis, studies that use technical indicators to explain cross-sectional stock returns have received significantly less attention.

Second, we contribute to the growing literature that considers new approaches to cross-sectional asset pricing. A large body of literature has uncovered a growing number of new factors that can be used in cross-sectional asset pricing. For example, Bhandari (1988) finds that firms with higher leverage ratios have higher returns than those with lower leverage ratios. Similarly, Rosenberg, Reid, and Lanstein (1998) present evidence that firms with higher book-to-market ratios generate higher returns than those with lower book-to-market ratios. More recently, Green, Han, and Zhang (2017) explore 94 firm characteristics and find that approximately ten of these characteristics generate consistent estimation ability. Yan and Zheng (2017) investigate 18,000 fundamental signals and find that many of them can significantly explain cross-sectional stock returns even after accounting for data mining. Moreover, Han, He, Rapach, and Zhou (2020) seek to improve cross-sectional forecasts based on fundamental variables using machine learning tools that shrink a comprehensive set of firm characteristics. They measure the cross-sectional forecast accuracy based on their newly created cross-sectional out-of-sample R^2 statistic.

Our paper is different to the majority of technical analysis papers cited above in that we consider a cross-sectional rather than a time-series setting. We differ from the cross-sectional asset pricing literature mentioned above because we investigate technical indicators rather than firm fundamental variables. We do, however, apply the methodology advances of Han, He, Rapach, and Zhou (2020) in our setting.

Our focus on technical indicators in a cross-sectional context is grounded in the literature. Many top traders and investors use technical analysis partially or exclusively (Schwager, 1993; Lo and Hasanhodzic, 2010). Furthermore, when information about stocks is uncertain, investors tend to rely more heavily on technical signals as fundamental signals can be imprecise (Han, Yang, and, Zhou, 2013). Covel (2006) advocates the use of technical analysis rather than learning any fundamental information on the market, and they cite examples of large and successful hedge funds to support their argument.

Our results show that the 14 individual technical indicators are factors that provide unique information beyond those most-documented traditional asset pricing determinants in estimating the cross-sectional stock returns. Our results support our assumption that technical indicators play an important role in estimating cross-sectional stock returns. We find that technical indicators and the SOLS model estimate cross-sectional stock returns consistently over time based on the conventional time-series out-of-sample R^2 statistics and cross-sectional out-of-sample R^2 statistics developed by Han, He, Rapach, and Zhou (2020). Moreover, for at least 80% of firms, the technical indicators show stronger cross-sectional estimation power than the Fama and French (1993) three factors.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 is devoted to the method. Section 4 reports the empirical analysis results. We conclude in Section 5.

3.2. Literature Review and Background

An extensive body of literature attempts to explain the cross-sectional expected returns over the past four decades. The capital asset pricing model (CAPM) is one of the most well-known tests that finds that higher expected returns deliver higher systematic risk. Approximately at the same time, Sharpe (1964), Lintner (1965), and Mossin (1966) introduce the one-factor capital asset pricing model (CAPM), which builds on Harry Markowitz's earlier work on diversification and modern portfolio theory and use asset market beta to measure this systematic risk. Fama and MacBeth (1973) examine its efficiency and confirm that beta is related to both risk and expected returns. Kraus and Litzenberger (1976) test the market factor and incorporate the effect of skewness on the valuation of cross-sectional expected returns. Subsequently, numerous of studies have attempted to explain the cross-sectional expected returns.

The early time listed cross-sectional expected returns determined variables include size (Banz, 1981), leverage (Bhandari and Chand, 1988), earnings price ratio (Basu, 1983), and book-to-market ratio (Rosenberg, Reid, and Lanstein, 1985). Banz (1981) finds a negative relationship between equity returns and firm size. Basu (1977) proves that the equity with a higher earnings price ratio earns a higher expected return than that calculated based on CAPM. Fama and French (1992) construct the most-documented three-factor model and find that market equity (ME) size and the book-to-market ratio capture much of the cross-section of expected stock returns in addition to market beta. Carhart (1997) proposes a four-factor model by adding the momentum factor to explain equity return differences based on the momentum effect. Fama and French (1992) introduce the five-factor asset pricing model by adding profitability and investment factors into their three-factor model.

From the aforementioned early pioneering works on cross-sectional expected stock returns, we can see that size, value, and momentum are the most prominent explanatory factors. Additionally, we find that a single economic risk factor does not adequately explain the cross-sectional variation in average stock returns. However, the argument on which characteristics provide independent explanatory information about expected returns continues. A growing body of evidence indicates that expected cross-sectional returns are consistent with various firm characteristics. Subrahmanyam (2010) claims that more than 50 variables are correlated with cross-sectional stock returns. Green, Hand, and Zhang (2017) examine the explanative ability of 94 characteristics and find that most of them fail to provide dependent information for the cross-sectional expected returns. Chordia, Goyal, and Shanken (2011) simultaneously evaluate the performance of betas and some firm characteristics and find that both explain the variation in cross-sectional stock returns, but the characteristics contribute more.

Macroeconomic variables have also been tested by different studies to explain cross-sectional stock returns. Chen, Roll, and Ross (1986) investigate whether the macroeconomic variables (term premium, default premium, inflation, and industrial production growth) can explain expected stock returns and find that systematic economic news significantly influences stock returns. Breeden (1979) proposes the consumption capital asset pricing model (CCAPM), which relates asset returns to their covariances with the marginal utility of consumption. Lettau and Ludvigson (2001a, 2001b) argue that the cointegration ratio of consumption, wealth, and income (cay) can further improve cross-sectional pricing performance over CCAPM. Furthermore, Yogo (2006) shows that non-separable utility also helps explain stock returns.

The explanatory of cross-sectional stock return is also investigated in other financial markets (Solnik, 1974; Grauer, Litzenberger, and Stehle, 1976; Sercu, 1980; Stulz, 1981; and Errunza and Losq, 1985). Chan, Hamao, and Lakonishok (1991) find a significant relationship between earnings yield, size, the book to market ratio, and cash flow yield and expected returns in the Japanese market. Capaul, Rowley, and Sharpe (1993) claim that the BM effect also exists in European countries (France, Germany, Switzerland, and the U.K.). After exploring 12 non-US major markets and emerging markets, Fama and French (1998) find that value stocks have significantly higher expected returns than growth stocks do. Hou, Karolyi, and Kho (2011) conduct a more comprehensive study that expands the analysis sample to 49 countries. However, in contrast with macroeconomic variables and firm characteristics, technical indicators receive much less attention in explaining cross-sectional stock returns. Han, Zhou, and Zhu (2016) construct a moving average-based trend factor that incorporates multiple price signals and find that it performs well in explaining cross-sectional stock returns.

3.3. Data

We source the monthly equity returns of all firms listed on NYSE, AMEX, and NASDAQ markets from CRSP. The monthly equity returns data span from January 1926 to December 2020, where January 1926 is the earliest month to obtain stock returns from CRSP. We remove firms with stock returns lower than -100% and exclude delisted firms. Our estimation is based on 60-month rolling regressions for the historical mean and smoothed OLS models. Therefore, we delete firms with fewer than 60 monthly return observations to ensure sufficient data in each regression. Since the construction of technical indicators needs past 12 months' observations, and we apply them in the 60-month rolling regression in the smoothed OLS model. Our first estimation month is January 1932, and our cross-sectional out-of-sample return forecasts span from January 1932 to December 2020. The whole out-of-sample period is divided into three sub-periods of around 30 years each for the subsample analysis.

We also collect data on the Fama-French (1993) three-factor and Carhart (1997) four-factor models from Kenneth French's website[8]. Besides, we obtain data on the Fama-French (2016) five-factor model from Compustat to construct size, book-to-market value, operating profitability, and investment factors for all the individual firms. Because the book-to-market value is robustly available in 1963, the estimation based on the Fama French three-factor model starts from January 1963 and ends in December 2020. The construction of 14 firm-level technical variables is described in Appendix 1.1.

3.4. Method

3.4.1. Smoothed OLS (SOLS) Model

The standard framework to examine the cross-sectional expected stock returns that apply multiple technical indicators is generally based on the OLS regression model as follow:

$$r_{i,t} = \alpha_t + \sum_{j=1}^{J} \beta_{j,t} x_{i,j,t-1} + \varepsilon_{i,t} \quad \text{for } \ i = 1, \dots, N_t, \tag{3.1}$$

where $r_{i,t}$ is the equity return for stock i in month t, and $x_{i,j,t-1}$ is the jth technical indicator for stock i in month t - 1. J = 14, for we apply 14 technical indicators in each regression, and N_t represents the number of available firms for month t.

The cross-sectional estimated return for stock i in the month t + 1 based on equation

[8] Many appreciate for Kenneth French to provide the data on his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

(3.1) is given by:

$$\hat{r}_{i,t+1}^{OLS} = \hat{\alpha}_t + \sum_{j=1}^{J} \hat{\beta}_{j,t} x_{i,j,t} \quad \text{for} \quad i = 1, \dots, N_{t+1}, \tag{3.2}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_{j,t}$ are the estimated coefficients of α_t and $\beta_{j,t}$ in equation (3.1). J = 14 in equation (3.1) leads to overfitting concern. For mitigating this overfitting problem, we follow Han, He, Rapach, and Zhou (2020) to apply the smoothed OLS (SOLS) model[9] by taking the time-series average of the cross-sectional OLS estimated coefficients $\hat{\alpha}_t$ and $\hat{\beta}_{j,t}$ of equation (3.2) over a specific month period as follow:

$$\hat{r}_{i,t+1}^{SOLS} = \tilde{\alpha}_t + \sum_{j=1}^{J} \tilde{\beta}_{j,t} x_{i,j,t} \quad \text{for} \quad i = 1, \dots, N_{t+1}, \tag{3.3a}$$

where

$$\tilde{\alpha}_t = \frac{1}{K} \sum_{k=0}^{K-1} \hat{\alpha}_{t-k}, \tag{3.3b}$$

$$\tilde{\beta}_{j,t} = \frac{1}{K} \sum_{k=0}^{K-1} \hat{\beta}_{j,t-k}, \tag{3.3c}$$

K is the length of the smoothing window. The SOLS model reduces to the OLS model by taking K = 1, and we apply a 60-month (K = 60) smoothing window in this paper. The smoothed OLS model is a simple and efficient method to guard against the overfitting problem in the high-dimension OLS regression. It stabilizes the coefficients by smoothing the estimated coefficients

[9] This method is consistent with Haugen and Baker (1996), Lewellen (2015), and Green, Hand, and Zhang (2017).

over time and thus reduces the influence of estimation noise and helps to avoid the overfitting problem in the cross-sectional equity returns regression.

The three-factor model (Fama French, 1993) is the widely used cross-sectional return model; we thus consider it as our benchmark:

$$r_{i,t} = a_t + b_t^{beta} x_{i,t-1}^{beta} + b_t^{cap} x_{i,t-1}^{cap} + b_t^{bm} x_{i,t-1}^{bm} + \varepsilon_{i,t} \quad \text{for } i = 1, \dots, N_t, \tag{3.4}$$

where $r_{i,t}$ is the equity return for stock *i* in month *t*; $x_{i,t-1}^{beta}$ is the beta calculated by the covariance between individual stock returns and market returns divided by the variance of market returns in month *t* - 1 by using the past sixty-month rolling window (*t* - 61 to *t* - 1). $x_{i,t-1}^{cap}$ is the market capitalization of firm *i*, calculated by stock price times shares outstanding in month *t* - 1. $x_{i,t-1}^{bm}$ is the book-to-market value evaluated by the book value of stock *i* divided by its market capitalization in month *t* - 1. N_t represents the number of available firms for month *t*. The estimated return of stock *i* in month *t* + 1 computed by the cross-sectional three-factor model based on equation (3.4) is:

$$\hat{r}_{i,t+1}^{FF3} = \hat{a}_t + \hat{b}_t^{beta} x_{i,t}^{beta} + \hat{b}_t^{cap} x_{i,t}^{cap} + \hat{b}_t^{bm} x_{i,t}^{bm}, \tag{3.5}$$

where $\hat{a}_t$, $\hat{b}_t^{beta}$, $\hat{b}_t^{cap}$, and $\hat{b}_t^{bm}$ are the estimated coefficients of a_t, b_t^{beta}, b_t^{cap}, and b_t^{bm} in equation (3.4).

3.4.2. Evaluation

To ascertain the performance of cross-sectional stock returns model, Han, He, Rapach, and Zhou (2020) introduce the cross-sectional out-of-sample R^2 (R_{CSOS}^2), which is analogous to the conventional time-series out-of-sample (R_{TSOS}^2) introduced by Campbell and Thompson

(2008) but provide insight into the cross-sectional stock return evaluation. We comprehensively compare both out-of-sample evaluation metrics in this section.

3.4.2.1. Cross-Sectional Mean Squared Error (MSE) and Cross-sectional $\mathbf{R^2_{OS}}$ ($\mathbf{R^2_{CSOS}}$)

The value-weighted cross-sectional mean squared error introduced by Han, He, Rapach, and Zhou (2020) is defined as follows:

$$MSE_i^h = \frac{1}{n_t}\sum_{i=1}^{n_t} w_{i,t}[(r_{i,t} - \bar{r}_t) - (\hat{r}^h_{i,t|t-1} - \bar{\hat{r}}^h_{t|t-1})]^2 \quad \text{for } t = 1, \ldots, T, \tag{3.6a}$$

where

$$\bar{r}_t = \sum_{i=1}^{n_t} w_{i,t} r_{i,t}, \tag{3.6b}$$

$$\bar{\hat{r}}^h_{t|t-1} = \sum_{i=1}^{n_t} w_{i,t}\hat{r}^h_{i,t|t-1}, \tag{3.6c}$$

and $w_{i,t} \geq 0$ is the weight for stock i calculated by the proportional market capitalization of firm *i* at the end of month $t-1$. $\hat{r}^h_{i,t|t-1}$ represents the estimated stock return by the SOLS model (*h* = SOLS) from equation (3.3a) or the competing Fama French three-factor model (*h* = FF3) from equation (3.5). In the cross-sectional context, instead of taking the historical mean model as a benchmark, Han, He, Rapach, and Zhou (2020) use the value-weighted cross-sectional mean value as the naïve benchmark:

$$\hat{r}^{Naive}_{i,t|t-1} = \bar{r}_{t-1} \quad \text{for } i = 1, \ldots, n_t, \tag{3.7}$$

where n_t is the total number of available firms in month *t*. Thus, for the historical mean expected return, $\hat{r}_{i,t|t-1}^{Naive} - \bar{\hat{r}}_{i,t|t-1}^{Naive} = 0$ for $i = 1, \dots, n_t$, which translates into the value-weighted MSE of equation (3.6a) as follow:

$$MSE_t^{Naive} = \hat{\sigma}_{r,t}^2 = \frac{1}{n_t} \sum_{n=1}^{N_t} w_{i,t} (r_{i,t} - \bar{r}_t)^2 \quad \text{for } t = 1, \dots, T, \tag{3.8}$$

where $\hat{\sigma}_{r,t}^2$ represents the simply value-weighted cross-sectional return variance. Evaluating the equal-weighted cross-sectional MSE, we set equal weights for equations (3.6a), (3.6b), (3.6c), and (3.8) by taking $w_{i,t} = \frac{1}{n_t}$ (n_t is the number of available firms in month *t*). The value-weighted cross-sectional out-of-sample R_{CSOS}^2 in each month is defined based on comparing the value-weighted MSE of the SOLS model in equation (3.6a) and the value-weighted cross-sectional return variance in equation (3.4):

$$R_{CSOS,t}^2 = 1 - \frac{\sum_{i=1}^{n_t} w_{i,t} [(r_{i,t} - \bar{r}_t) - (\hat{r}_{i,t|t-1}^{SOLS} - \bar{\hat{r}}_{t|t-1}^{SOLS})]^2}{\sum_{n=1}^{n_t} w_{i,t} (r_{i,t} - \bar{r}_t)^2} \quad \text{for } t = 1, \dots, T, \tag{3.9}$$

where T represents the total number of $R_{CSOS,t}^2$ statistics. Evaluating the equal-weighted cross-sectional $R_{CSOS,t}^2$, we compare the equal-weighted MSE of the SOLS model with the simple equal-weighted cross-sectional return variance by replacing the value weight $w_{i,t}$ with the equal weight $\frac{1}{n_t}$ in equation (3.9). After that, we take the time-series average of all the $R_{CSOS,t}^2$ statistics based on the Fama-MacBeth (1973) procedure:

$$R_{CSOS}^2 = \frac{1}{T} \sum_{t=1}^{T} R_{CSOS,t}^2, \tag{3.10}$$

Finally, we test $H_0: R_{CSOS}^2 = 0$ against the $H_A: R_{CSOS}^2 \neq 0$ using heteroskedasticity and autocorrelation consistent *t*-statistics (Newey and West, 1987).

3.4.2.2. Time-Series Mean Squared Error (MSE) and Out-of-Sample $\mathbf{R^2}$

The most-documented Campbell and Thompson (2008) out-of-sample R^2 is calculated based on measuring the proportional reduction in the time-series mean squared error (MSE) for the smoothed OLS estimation vis-à-vis the historical average expected return, and the time-series mean squared error (MSE) measures accuracy based on the estimation deviations:

$$MSE_i^k = \frac{1}{T_i}\sum_{t=1}^{T_i}(r_{i,t} - \hat{r}_{i,t|t-1}^k)^2, \tag{3.11}$$

where $r_{i,t}$ is the actual return for stock i in month t and $\hat{r}_{i,t|t-1}^{SOLS}$ (k = SOLS), $\hat{r}_{i,t|t-1}^{HISM}$ (k = HISM), and $\hat{r}_{i,t|t-1}^{FF3}$ (k = FF3) are the expected return estimated by the SOLS, historical mean, and Fama French (1993) three-factor models, respectively. T_i is the total number of out-of-sample period observations for stock i. The value-weighted time-series MSE is evaluated by:

$$\overline{MSE}^k = \sum_{i=1}^{N}\omega_i MSE_i^k, \tag{3.12}$$

$\omega_i \geq 0$ is the weight for stock i calculated by the proportional averaged capitalization of firm i. For the equal-weighted MSE, we take $\omega_i = \frac{1}{N}$ in equation (3.12), where N is the total number of firms over the whole out-of-sample analysis. We calculate the positive proportion of the MSE difference between the historical mean model (Fama French three-factor model) and the SOLS model to evaluate the performance.

Finally, the conventional time-series out-of-sample R^2 (R_{TSOS}^2) statistics take the historical mean model as a benchmark and compare the relative error of the SOLS estimate and the historical average expected return based on the mean squared error (MSE) as follow:

$$R^2_{TSOS,i} = 1 - \frac{MSE_i^{SOLS}}{MSE_i^{HISM}}, \tag{3.13}$$

where MSE_i^{SOLS} (MSE_i^{HISM}) is the value, or equal-weighted time-series mean squared error of the smoothed OLS model (historical mean model) for stock i computed by equation (3.13). To assess the general firm expected return estimation, we take the simple average of the out-of-sample $R^2_{TSOS,i}$ statistic for all the firms:

$$\bar{R}^2_{TSOS} = \frac{1}{N}\sum_{i=1}^{N} R^2_{TSOS,i}, \tag{3.14}$$

where N represents the total number of firms, a positive value of $\bar{R}^2_{TSOS}$ indicates that the SOLS estimate outperforms the historical average estimation overall. In contrast, the negative value suggests an opposite role.

3.4.3. Profit-Making Strategy

We measure the economic value of the cross-sectional expected return by evaluating the profitability of the value (equal) weighted long-short portfolios constructed based on the ranking of estimated return for each stock. At the end of each month, we sort all the stocks into ten value-weighted (equal-weighted) portfolios based on their estimated returns for the next month, and we select firms with the highest (lowest) expected returns into the top (bottom) investment portfolio. We then buy stocks in the top portfolio and sell stocks in the bottom portfolio, holding this position for one month and rebalance the strategy monthly. For comparison, we take the equal-weighted market portfolio as the benchmark. After obtaining the monthly return of the constructed investment strategy, we compute the risk-adjusted returns by applying Carhart's (1997) four-factor model.

3.4.4. Decomposition of the Cross-Sectional Determinants

This section applies Hou and Loh's (2016) decomposition method to test whether the five cross-sectional stock returns determinants (momentum, size, book-to-market ratio, operating profit, and investment) contribute to the cross-sectional determination captured by the technical indicators. Momentum and the technical indicators capture the trend-following price movement. Thus, we raise the first question: whether momentum shares the cross-sectional determinant with the 14 technical indicators. Book-to-market ratio, size, operating profit, and investment are the most-documented determinants of cross-section stock returns which are also known as the pricing factors of the Fama French (2016) five-factor model. The second question is whether the cross-sectional explanatory power captured by the technical indicators is related to these four factors.

The decomposition methodology is based on the Fama-MacBeth (1973) cross-sectional regression. We first regress univariate cross-sectional regression between the individual stock returns and technical indicators:

$$r_{i,t} = \alpha_{j,t} + \theta_{j,t} x_{i,j,t-1} + \varepsilon_{i,j,t} \quad \text{for } i = 1, \dots, N_t, \tag{3.15}$$

where $r_{i,t}$ is the equity return for stock i in month t, and $x_{i,j,t-1}$ is the jth technical indicator for stock i at month t - 1. Next, we investigate the relationship between the technical indicators and the five candidate variables by regressing the individual technical indicator $x_{i,j,t-1}$ on each of the five selected candidate variables as follow:

$$x_{i,j,t-1} = a_{j,h,t-1} + \eta_{j,h,t-1} V_{i,h,t-1} + \epsilon_{i,j,h,t-1} \qquad \text{for } h = \text{MOM, BM, Size, OP, INV}, \tag{3.16}$$

where $V_{i,h,t-1}$ represents the five candidate variables of each firm i: momentums (h = MOM), the book to market ratio (h = BM), size (h = Size), operating profit (h = OP), and investment (h = INV). We apply four firm-level momentums based on the past 3, 6, 9, and 12 months. According to Fama and French (2016), the four firm-level factors are used. After that, we decompose $x_{i,j,t-1}$ into two orthogonal components based on the regression coefficients from equation (3.16) by following Hou and Loh (2016) as follow:

$$\theta_{j,h,t} = \frac{Cov(r_{i,t},\ x_{i,j,t-1})}{Var(x_{i,j,t-1})} = \frac{Cov[r_{i,t},\ (a_{j,h,t-1}+\eta_{j,h,t-1}V_{i,h,t-1}+\epsilon_{i,j,h,t-1})]}{Var(x_{i,j,t-1})}$$

$$= \frac{Cov(r_{i,t},\ \eta_{j,h,t-1}V_{i,h,t-1})}{Var(x_{i,j,t-1})} + \frac{Cov(r_{i,t},\ a_{j,h,t-1}+\epsilon_{i,j,h,t-1})}{Var(x_{i,j,t-1})}$$

$$= \theta^C_{j,h,t} + \theta^R_{j,h,t}. \tag{3.17}$$

where $\eta_{j,h,t-1}V_{i,h,t-1}$ $(a_{j,h,t-1} + \epsilon_{i,j,h,t-1})$ is the related (residual) component of $x_{i,j,t-1}$. We then use $\frac{\theta^C_{j,h,t}}{\theta_{j,h,t}}$ $(\frac{\theta^R_{j,h,t}}{\theta_{j,h,t}})$ to calculate the explained (residual) fractions for each of the 14 technical indicators by each of the five factors: momentums (h = MOM), size (h = Size), the book to market ratio (h = BM), operating profit (h = OP), and investment (h = INV). After that, we estimate the mean and variance of the fractions over the whole regression periods as:

$$\hat{E}(\frac{\theta^C_{j,h,t}}{\theta_{j,h,t}}) \approx \frac{\bar{\theta}^C_{j,h,t}}{\bar{\theta}_{j,h,t}}, \quad \hat{E}(\frac{\theta^R_{j,h,t}}{\theta_{j,h,t}}) \approx \frac{\bar{\theta}^R_{j,h,t}}{\bar{\theta}_{j,h,t}}, \tag{3.18a}$$

$$\widehat{Var}(\frac{\theta^C_{j,h,t}}{\theta_{j,h,t}}) \approx \frac{1}{T}\left(\frac{\bar{\theta}^C_{j,h,t}}{\bar{\theta}_{j,h,t}}\right)^2 (\frac{\sigma^2_{\theta^C_{j,h,t}}}{\bar{\theta}^{C\,2}_{j,h,t}} + \frac{\sigma^2_{\theta_{j,h,t}}}{\bar{\theta}_{j,h,t}^{\,2}} - 2\frac{\hat{\rho}_{\theta^C_{j,h,t},\theta_{j,h,t}}\sigma^2_{\theta^C_{j,h,t}}\sigma^2_{\theta_{j,h,t}}}{\bar{\theta}^C_{j,h,t}\bar{\theta}_{j,h,t}}), \tag{3.18b}$$

$$\widehat{Var}\left(\frac{\theta^R_{j,h,t}}{\theta_{j,h,t}}\right) \approx \frac{1}{T}\left(\frac{\bar{\theta}^R_{j,h,t}}{\bar{\theta}_{j,h,t}}\right)^2 \left(\frac{\sigma^2_{\theta^R_{j,h,t}}}{{\bar{\theta}^R_{j,h,t}}^2} + \frac{\sigma^2_{\theta_{j,h,t}}}{{\bar{\theta}_{j,h,t}}^2} - 2\frac{\hat{\rho}_{\theta^R_{j,h,t},\theta_{j,h,t}}\sigma^2_{\theta^R_{j,h,t}}\sigma^2_{\theta_{j,h,t}}}{\bar{\theta}^R_{j,h,t}\bar{\theta}_{j,h,t}}\right), \tag{3.18c}$$

and,

$$t_{\frac{\bar{\theta}^C_{j,h,t}}{\bar{\theta}_{j,h,t}}} = \frac{\frac{\bar{\theta}^C_{j,h,t}}{\bar{\theta}_{j,h,t}}}{\sigma\left(\frac{\bar{\theta}^C_{j,h,t}}{\bar{\theta}_{j,h,t}}\right)},\ t_{\frac{\bar{\theta}^R_{j,h,t}}{\bar{\theta}_{j,h,t}}} = \frac{\frac{\bar{\theta}^R_{j,h,t}}{\bar{\theta}_{j,h,t}}}{\sigma\left(\frac{\theta^R_{j,h,t}}{\theta_{j,h,t}}\right)}, \tag{3.18d}$$

We refer to Hu and Loh's (2016) paper to see more details.

3.5. Empirical Results

3.5.1. Correlations among technical indicators

This paper applies all the 14 technical indicators in predictive regression. To test the multicollinearity concerns in the estimation, we follow Green, Hand, and Zhou (2017) by applying the variance inflation factors (VIFs) of each technical indicator. Moreover, we follow them to set the VIFs cutoff to 7. Table 3.1 presents the averaged cross-sectional VIFs. To measure the cross-sectional level correlation of these 14 firm-level technical indicators, we calculate the monthly VIFs of each technical indicator and average the monthly VIFs to get the averaged cross-sectional VIFs. We can see that 13 out of 14 VIFs are smaller than 7.

Table 3.1. Averaged cross-Sectional VIFs

Variables	VIF	Variables	VIF
MA(1, 9)	6.5613	MOM(12)	2.5636
MA(1,12)	6.5613	VOL(1,9)	5.7721
MA(2,9)	6.5613	VOL(1,12)	4.6482
MA(2,12)	6.5613	VOL(2,9)	7.1672
MA(3,9)	4.7349	VOL(2,12)	5.8266
MA(3,12)	4.3078	VOL(3,9)	5.9252
MOM(9)	1.9471	VOL(3,12)	5.4320

This table presents the averaged cross-sectional VIF for each of the 14 technical indicators.

3.5.2. Cross-Sectional Performance of Technical Indicators

Table 3.2 reports the value- and equal-weighted cross-sectional R^2 statistics and the mean squared errors for the SOLS model and Fama French three-factor (FF3) estimation over the whole period and three (two) subsamples. The results suggest that technical indicators based on the SOLS model show strong ability in explaining the cross-sectional individual stock expected returns and significantly outperform the benchmark Fama French three-factor (FF3) models consistently over time. The value-weighted and equal-weighted cross-sectional out-of-sample R^2 statistics in Panel A and Panel B are positive and significant at the 1% level. The SOLS model has a smaller averaged MSE ($\overline{MSE}_{SOLS}$) than the naïve benchmark[10] ($\overline{MSE}_{NAIVE}$) for the full out-of-sample and the three subsamples.

In addition, we take the estimated results of the Fama French three-factor model as another benchmark and present the value-weighted and equal-weighted cross-sectional MSE results in Panel C and D, respectively. We can see that the SOLS model generates significantly smaller errors than the well-documented Fama French three-factor (FF3) model: the MSE differences between the SOLS model and FF3 model are all positive and significant at a 1% level in the last row of Panels C and D.

[10] Han, He, Rapach, and Zhou (2020) consider a naïve benchmark predictive model in the cross-sectional forecast, and its cross-sectional MSE is simply the cross-sectional return variance. Besides, the magnitude of R^2_{CSOS} is small in our analysis but relatively larger than the R^2_{CSOS} calculated by Han, He, Rapach, and Zhou (2020) in their study.

Table 3.2. Cross-sectional out-of-sample R^2

	Full Sample	Subsamples		
	1932:01-2020:12	1932:01-1959:12	1960:01-1989:12	1990:01-2020:12
		Panel A: Value-Weighted R^2_{CSOS} and MSE		
R^2_{CSOS}	0.594% [4.36]***	0.472% [3.18]***	0.451% [2.36]***	0.841% [2.65]***
$\overline{MSE}_{SOLS}$	0.647%	0.609%	0.556%	0.778%
$\overline{MSE}_{NAIVE}$	0.653%	0.603%	0.559%	0.790%
$\overline{MSE}_{D\imath f}$	0.006% [5.53]***	0.002% [3.11]***	0.003% [3.25]***	0.012% [4.32]***
		Panel B: Equal-Weighted R^2_{CSOS} and MSE		
R^2_{CSOS}	1.121% [19.27]***	0.361% [4.61]***	0.892% [10.09]***	2.026% [18.63]***
$\overline{MSE}_{SOLS}$	2.011%	1.442%	1.513%	3.005%
$\overline{MSE}_{NAIVE}$	2.035%	1.445%	1.523%	3.063%
$\overline{MSE}_{D\imath f}$	0.024% [15.43]***	0.003% [3.44]***	0.009% [9.51]***	0.058% [15.44]***
	1963:01-2020:12		1963:01-1989:12	1990:01-2020:12
		Panel C: Value-Weighted MSE (Fama French Three-Factor Model)		
$\overline{MSE}_{SOLS}$	0.662%		0.548%	0.761%
$\overline{MSE}_{FF3}$	0.722%		0.599%	0.828%
$\overline{MSE}_{D\imath f}$	0.060% [7.08]***		0.051% [6.76]***	0.0672% [4.70]***
		Panel D: Equal-Weighted MSE (Fama French Three-Factor Model)		
$\overline{MSE}_{SOLS}$	2.275%		1.430%	3.006%
$\overline{MSE}_{FF3}$	2.371%		1.481%	3.141%
$\overline{MSE}_{D\imath f}$	0.096% [8.29]***		0.051% [6.41]***	0.135% [6.66]***

This table reports the cross-sectional out-of-sample R^2 statistics (R^2_{CSOS}) and averaged mean squared errors (MSE) for the SOLS model ($\overline{MSE}_{SOLS}$) and Fama French three-factor estimation ($\overline{MSE}_{FF3}$). Panels A and B (C and D) reports the cross-sectional performance for the SOLS (Fama French three-factor) model, and we report the results for the three (two) subsamples from the third (fourth) to the fifth column. R^2_{CSOS} in the first row of Panel A (B) shows the value (equal)-weighted out-of-sample R^2 statistics. $\overline{MSE}_{SOLS}$ in the second (first) rows of Panels A and B (C and D) represent the value-weighted and equal-weighted mean squared errors for the SOLS model based on 14 joint technical indicators. $\overline{MSE}_{NAIVE}$ in the third row of Panels A and B is the naïve benchmark value and equal-weighted mean squared errors introduced by Han, He, Rapach, and Zhou (2020), which is simply the cross-sectional return variance. $\overline{MSE}_{FF3}$ in the second row of Panels C and D are the value-weighted and equal-weighted mean squared errors based on the estimation of the Fama French three-factor model. We present the averaged MSE difference ($\overline{MSE}_{D\imath f}$) between the SOLS model and the competing model in the last row of each panel. *** indicates statistical significance at the 1% level.

Table 3.3 further assesses the performance of the SOLS, historical mean, and Fama French (1993) three-factor models by applying the traditional value- and equal-weighted time-series out-of-sample R^2 statistics and mean squared errors. Panels A, B, and C (D, E, and F) show the cross-sectional performance comparison between the SOLS model and historical mean (FF3) model over the entire sample 1932:01 (1963:01) to 2020:12 and three (two) subsamples: 1932:01 to 1959:12, 1960:01 to 1989:12, and 1990:01 to 2020:12 (1963:01 to 1989:12, and 1990:01 to 2020:12)[11]. The positive and significant value- and equal-weighted out-of-sample R^2 statistics ($\bar{R}^2_{TSOS}$) in the first row of Panels A and B suggest that the SOLS model outperforms the historical mean model in explaining the cross-sectional stock expected returns over the whole out-of-sample and three subsamples.

Besides, the SOLS model generates a lower error than the historical mean model. The value- and equal-weighted mean squared errors for the SOLS model ($\overline{MSE}_{SOLS}$) in the second row of Panels A and B are smaller than that for the historical mean model ($\overline{MSE}_{HISM}$) over the entire sample and three subsamples. Moreover, we evaluate the proportion of positive MSE difference (MSE_{HISM} - MSE_{SOLS}) between the historical mean model and the SOLS model in Panel C. The results show that 87.93% (80.01%, 87.43%, and 82.31%) firms produce lower MSE by using the SOLS model than the historical mean model over the entire sample (three subsamples) from 1932:01 to 2020:12 (1932:01 to 1959:12, 1960:01 to 1989:12, and 1990:01 to 2020:12).

[11] The cross-sectional period of the Fama French three-factor model covers January 1963 to December 2020 because the book-to-market value only becomes robustly available in 1963. We divide it into two subsamples: 1963:01 to 1989:12 and 1990:01 to 2020:12.

Table 3.3. Time-series out-of-sample R^2

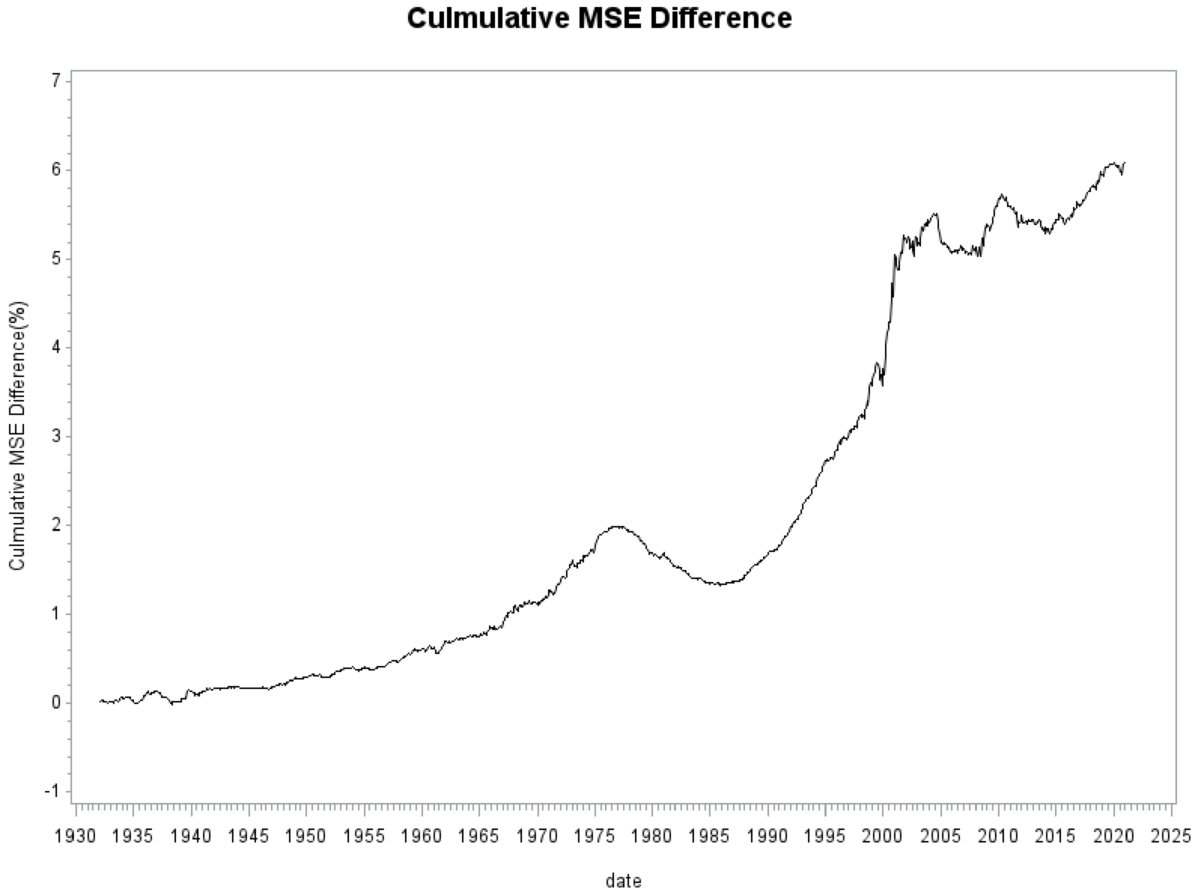
	Full Sample	Subsamples		
	1932:01-2020:12	1932:01-1959:12	1960:01-1989:12	1990:01-2020:12
	Panel A: Value-Weighted R^2_{TSOS} and MSE (Historical Mean)			
$\bar{R}^2_{TSOS}$	4.89%	2.69%	3.20%	3.98%
$\overline{MSE}_{SOLS}$	1.49%	0.84%	1.02%	1.31%
$\overline{MSE}_{HISM}$	1.58%	0.87%	1.09%	1.38%
	Panel B: Equal -Weighted R^2_{TSOS} and MSE (Historical Mean)			
$\bar{R}^2_{TSOS}$	4.24%	3.74%	2.91%	3.70%
$\overline{MSE}_{SOLS}$	3.68%	2.37%	1.86%	3.34%
$\overline{MSE}_{HISM}$	3.86%	2.41%	1.95%	3.49%
	Panel C: Positive percentage of MSE-F			
P_MSEF	87.93%	80.01%	87.43%	82.31%
	Full Sample	Subsamples		
	1963:01-2020:12		1963:01-1989:12	1990:01-2020:12
	Panel D: Value-Weighted MSE (Fama French Three-Factor Model)			
$\overline{MSE}_{SOLS}$	1.39%		0.97%	1.28%
$\overline{MSE}_{FF3}$	1.72%		1.21%	1.62%
	Panel E: Equal-Weighted MSE (Fama French Three-Factor Model)			
$\overline{MSE}_{SOLS}$	3.82%		2.79%	5.62%
$\overline{MSE}_{FF3}$	4.15%		3.02%	5.98%
	Panel F: Positive percentage of MSE-F			
P_MSEF	87.90%		82.76%	86.40%

This table reports the traditional time-series out-of-sample R^2 statistics and averaged mean squared errors for the SOLS model ($\overline{MSE}_{SOLS}$), historical mean model ($\overline{MSE}_{HISM}$), and Fama French three-factor estimation ($\overline{MSE}_{FF3}$). Panels A, B, and C (D, E, and F) show the cross-sectional performance comparison between the SOLS model and historical mean (Fama French three-factor) model over the full sample 1932:01(1963:01) to 2020:12 and three (two) subsamples: 1932:01 to 1959:12, 1960:01 to 1989:12, and 1990:01 to 2020:12 (1963:01 to 1989:12, and 1990:01 to 2020:12). $\bar{R}^2_{TSOS}$ in the first row of Panel A (B) shows the value (equal)-weighted time-series out-of-sample R^2 statistics. $\overline{MSE}_{SOLS}$ in the second (first) row of Panels A and B (E and F) represent the equal-weighted and value-weighted mean squared errors for the SOLS model based on 14 joint technical indicators. $\overline{MSE}_{HISM}$ ($\overline{MSE}_{FF3}$) in the third (second) row of Panels A and B (E and F) is the value-weighted and equal-weighted mean squared errors of the historical mean (Fama French three-factor) model. P_MSEF in Panel C (F) represents the positive percentage of MSE difference between the historical mean (Fama French three-factor) model and the SOLS model.

The first and second rows of Panel D (E) show the value- (equal)-weighted MSE for the SOLS and FF3 models. We report the positive percentage of their difference in Panel F. The results show that the SOLS model outperforms the Fama French three-factor model over the entire sample and the two subsamples by producing lower error. We can observe that all the value- and equal-weighted MSEs are lower for the SOSL model than those for the FF3 model. Moreover, the P_MSEF in Panel F shows that 87.90% (82.76%, and 86.40%) firms produce lower MSE by using the SOLS model than the FF3 model over the entire sample (two subsamples) from 1932:01 to 2020:12 (1963:01 to 1989:12, and 1990:01 to 2020:12).

Figure 1 provides the time variation in out-of-sample cross-sectional returns performance based on the SOLS model that utilizes the 14 joint technical indicators. The figure portrays the cumulative value-weighted cross-sectional mean squared error difference between the SOLS and the historical mean estimation. To evaluate the difference between SOLS and the historical mean model over time, we first calculate the MSE difference between the Han, He, Rapach, and Zhou (2020) defined value-weighted cross-sectional mean squared error of these two models. We then cumulate the MSE difference over the entire out-of-sample period from 1932:01 to 2020:12. An increasing trend of the line implies a better performance of the SOLS model, while a decreasing trend suggests a stronger determinant of the prevailing mean model.

Figure 1. Cumulative cross-sectional MSE difference (1932:01–2020:12)



The figure depicts the out-of-sample performance of the cross-sectional SOLS regression model by using the cumulative value-weighted cross-sectional mean squared error (MSE) difference between the SOLS model and the historical mean model. An increasing trend of the line implies a better performance of the SOLS model, while a decreasing trend suggests a stronger ability of the prevailing mean model. The whole out-of-sample period spans from January 1932 to December 2020.

The cumulative squared error difference displays a solid upward trend throughout the out-of-sample period, indicating that the SOLS model appears to generate consistently significant out-of-sample cross-sectional equity expected returns over time. We can see that the cumulative squared error difference steadily increases to the value of approximately 2% from 1932 to 1973, and decrease to 1.3% in 1986, then keep increasing at a faster rate to around 5.8% in 2005 and keep growing at a fluctuating increase rate to around 6.2% at the end of the estimation period (2020).

3.5.3. Economic Value

Table 3.4 provides the summary statistics for the monthly profits of the value- and equal-weighted long-short portfolios based on the SOLS estimates and simple equal-weighted market portfolios over the whole sample and three subsamples (1932:01 to 1959:12, 1960:01 to 1989:12, and 1990:01 to 2020:12). Mean, STD, Skewness, Kurtosis, and Ann.SR represents the monthly mean, standard deviation, skewness, kurtosis, and annual Sharpe ratio, respectively. It is evident that the equal-weighted long-short portfolio (in Panel A) and the value-weighted long-short portfolio (in Panel B) based on the investment strategy that buys the best past performing firms and sells the worst past performing firms generate a remarkably higher monthly profit and lower standard deviation than the naïve market portfolio returns (in Panel C).

The equal- (value-) weighted long-short portfolio for the SOLS expected return in the first row of Panel A (B) has an average return of 4.22% (2.96%) over the total investment period, which is over four (two) times higher than the monthly average return of 1.02% for the simple market portfolio in Panel C. However, the relative monthly standard deviation is lower for the equal- and value-weighted long-short portfolios (4.71% and 3.40%) than that for the market portfolio (5.23%), implying a higher annualized Sharpe ratio of 2.90 and 2.73 for the equal- and value-weighted long-short portfolios than the 0.50 Sharpe ratio for the market portfolio.

The equal (value)-weighted long-short portfolio based on the SOLS estimate in Panel A (B) generates a monthly average return of 1.42%, 2.93% and 7.98% (1.27%, 2.33%, and 5.08%), and standard deviation of 3.54%, 2.41% and 4.88% (2.68%, 2.64%, and 3.53%) for the three subsamples, respectively, which translate to an annual Sharpe ratio of 0.74, 1.96 and 3.11 (0.87, 1.34, and 2.69). As a benchmark, the market portfolio in Panel C of Table 3.2 has much lower average returns (1.26%, 0.91%, and 0.92%) and higher standard deviations (6.87%, 4.33%, and 4.23%) for the first and second subsamples, which produce lower Sharpe ratios (0.34, 0.18, and 0.32) than that for the equal and value-weighted long-short portfolios.

The skewness and kurtosis in the fourth and fifth column of Table 3.4 suggest that the equal- and value-weighted long-short portfolios based on the SOLS estimation have higher probabilities of generating extremely positive returns than the market portfolio. The skewness is 1.59 and 1.04 for the equal (value)-weighted long-short portfolio over the entire sample, higher than the market portfolio skewness of 0.66. Besides, the kurtosis in Panel A (B) is 5.76 (3.41) for the equal (value)-weighted long-short portfolio over the whole sample, which is much lower than for the market portfolio kurtosis of 10.72 in Panel C. Both cases suggest that the equal- and value-weighted long-short portfolios' returns are more likely to follow a normal distribution.

Table 3.4. Long-short performance

Period	Mean	STD	Skewness	Kurtosis	Ann. SR
Panel A: Equal-Weighted Long-Short Portfolio					
1932:01-2020:12	4.22%	4.71%	1.59	5.76	2.90
1932:01-1959:12	1.42%	3.54%	3.47	31.38	0.74
1960:01-1989:12	2.93%	2.41%	0.48	0.67	1.96
1990:01-2020:12	7.98%	4.88%	1.28	3.84	3.11
Panel B: Value-Weighted Long-Short Portfolio					
1932:01-2020:12	2.96%	3.40%	1.04	3.41	2.73
1932:01-1959:12	1.27%	2.68%	0.71	3.45	0.87
1960:01-1989:12	2.33%	2.64%	0.58	0.94	1.34
1990:01-2020:12	5.08%	3.53%	1.27	4.20	2.69
Panel C: Market Portfolio					
1932:01-2020:12	1.02%	5.23%	0.66	10.72	0.50
1932:01-1959:12	1.26%	6.87%	1.09	10.10	0.34
1960:01-1989:12	0.91%	4.33%	-0.28	2.35	0.18
1990:01-2020:12	0.92%	4.23%	-0.55	1.22	0.32

This table reports the summary statistics, including mean, standard deviation (STD), skewness, kurtosis, and annual Sharpe ratio (Ann. SR) of the monthly profits for equal (value)-weighted long-short portfolio constructed from the out-of-sample estimation of cross-sectional stock returns based on the SOLS model and market portfolio. We present the equal (value)-weighted long-short portfolio results based on the SOLS estimate in Panel A (B) and the results for the market portfolio in Panel C. The first row of each panel shows the summary statistics for the full 1932:01 to 2020:12 period, and the second to the last row reports the results for the three subsamples periods (1932:01 to 1959:12, 1960:01-1989:12, and 1990:01-2020:12).

Next, we examine whether the well-documented Carhart (1997) four-factor model can explain the profits generated by equal- and value-weighted long-short portfolios based on the SOLS estimation. Table 3.5 reports the estimates of the monthly alphas and the four factors' exposures, which include market (MKT), size (SMB), value (HML), and momentum (WML) of the Carhart (1997) model over the entire out-of-sample period (1932:01 to 2020:12) and the subsamples from 1932:01 to 1959:12, 1960:01 to 1989:12, and 1990:01 to 2020:12. The equal- and value-weighted long-short portfolios based on the SOLS model consistently generate a sizable risk-adjusted return over time. The second column of Panel A (B) shows that the monthly alpha is 4.24% (3.02%) for the equal (value)-weighted portfolio over the full sample and 1.25%, 2.91%, and 7.87% (1.25%, 2.36%, and 5.31%) for the three subsample periods, respectively, all of which are statistically significant at the 1% level.

Besides, both the equal- and value-weighted long-short portfolios exhibits positive but essentially zero exposure to the market (MKT) factor. However, the equal-weighted long-short portfolio in Panel A produces significant positive exposures to the size (SMB) factor and significant negative exposure to the momentum (WML) factor. The value-weighted long-short portfolio in Panel B exhibits insignificant exposure to the size (SMB) and value (HML) factors but show negative and significant exposure to the momentum (WML) factor for the full and three subsamples, all of which are statistically significant at 1% level. Moreover, the last column of Panel A indicates that the Carhart (1997) four-factor model can explain 7.50% (3.91%) of the equal (value)-weighted long-short portfolio return movement for the whole out-of-sample estimation, and 20.15%, 6.94%, and 13.68% (8.01%, 6.30%, and 5.53%) for the three subsamples, respectively.

Table 3.5. Alphas and factor exposure

Period	alpha	MKT	SMB	HML	WML	R^2
Panel A: Equal-Weighted Portfolio Risk-Adjusted Returns						
1932.01-2020.12	4.24%	0.07%	0.21%	-0.07%	-0.10%	7.50%
	[29.31]***	[2.26]**	[4.57]***	[-1.52]	[-5.00]***	
1932.01-1959.12	1.25%	0.04%	0.26%	0.09%	-0.05%	20.15%
	[6.90]***	[0.97]	[4.54]***	[1.56]	[-1.92]**	
1960.01-1989.12	2.91%	0.03%	0.19%	0.04%	-0.03%	6.94%
	[21.54]***	[0.87]	[3.96]***	[0.68]	[-1.36]	
1990.01-2020.12	7.87%	0.15%	0.29%	-0.00%	-0.14%	13.68%
	[31.67]***	[2.50]***	[3.63]***	[-0.04]	[-4.34]***	
Panel B: Value-Weighted Portfolio Risk-Adjusted Returns						
1932.01-2020.12	3.02%	0.00%	0.04%	-0.00%	-0.08%	3.91%
	[28.37]***	[0.27]	[1.31]	[-0.05]	[-5.26]***	
1932.01-1959.12	1.25%	0.00%	0.03%	0.06%	-0.05%	8.01%
	[8.49]***	[0.16]	[0.69]	[1.26]	[-2.66]***	
1960.01-1989.12	2.36%	0.07%	0.06%	0.13%	-0.08%	6.30%
	[15.87]***	[2.04]**	[1.09]	[2.17]**	[-3.06]***	
1990.01-2020.12	5.31%	-0.06%	0.12%	-0.03%	-0.10%	5.53%
	[26.81]***	[-1.13]	[1.90]*	[-0.46]	[-4.07]***	

This table reports the monthly risk-adjusted returns of the Carhart four-factor model for the equal and value-weighted long-short portfolios constructed by the out-of-sample estimate of cross-sectional stock expected returns based on the SOLS model. MKT is the “market excess return” factor; SMB is the “small firm size minus big firm size” factor; HML is the “high firm value minus low firm value” factor; WML is the “winner minus loser” momentum factor. The first row of each panel shows the full sample estimation results for the equal and value-weighted long-short portfolios, and the third to the fifth rows report the results for the three subsamples. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

3.5.4. Decomposition Analysis

We use Hou and Loh's (2016) covariance decomposition approach to explore whether the well-known factors (momentum, size, book-to-market ratio, operating profit, and investment) share the information of individual technical indicators in explaining the cross-sectional expected stock returns.

Table 3.6 measures the fraction of the cross-sectional expected return determinant of technical indicators captured by the four momentums, evaluated based on individual firm returns over the past 3, 6, 9, and 12 months. The 14 technical variables and the four momentums are constructed based on individual-level trend-following rules. However, we can see that all the four momentums fail to contribute to the explanatory power of the 14 technical variables in explaining cross-sectional equity expected returns. The explained fractions, *E(C/Y)*, attributable to MOM3, MOM6, and MOM9 in Panels A, B, and C are primarily negative and insignificantly related to the cross-sectional determinant captured by the 14 technical variables, except for the technical variable VOL (1,9), which is positive but statistically insignificant. Moreover, the results in Panel D show that 13 out of 14 of the fractions are small and insignificantly positive, and the fraction for VOL (1,9) is negative and insignificant, which suggest that MOM12 also fails to share the explanatory information of all the technical indicators in explaining cross-sectional stock expected returns.

Table 3.6. Decomposition: momentum factors

Indicators	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)
	Panel A: MOM3		Panel B: MOM6		Panel C: MOM9		Panel D: MOM12	
MA(1, 9)	-0.70 [-1.81]*	1.70 [4.38]***	-0.38 [-1.17]	1.37 [4.26]***	-0.13 [-0.58]	1.13 [4.99]***	0.01 [0.09]	0.99 [6.61]***
MA(1, 12)	-0.55 [-1.97]**	1.55 [5.52]***	-0.33 [-1.25]	1.33 [5.08]***	-0.12 [-0.60]	1.12 [5.48]***	0.01 [0.07]	0.99 [6.96]***
MA(2, 9)	-0.60 [-1.98]**	1.60 [5.29]***	-0.36 [-1.26]	1.36 [4.77]***	-0.12 [-0.59]	1.12 [5.48]***	0.02 [0.13]	0.98 [7.29]***
MA(2, 12)	-0.49 [-2.10]**	1.49 [6.36]***	-0.32 [-1.34]	1.32 [5.51]***	-0.12 [-0.62]	1.12 [5.76]***	0.01 [0.09]	0.98 [7.31]***
MA(3, 9)	-0.54 [-1.92]*	1.54 [5.46]***	-0.35 [-1.19]	1.35 [4.56]***	-0.12 [-0.53]	1.12 [5.14]***	0.04 [0.27]	0.96 [6.91]***
MA(3, 12)	-0.42 [-2.09]**	1.42 [7.07]***	-0.31 [-1.33]	1.31 [5.64]***	-0.12 [-0.61]	1.12 [5.76]***	0.02 [0.19]	0.98 [7.28]***
MOM(9)	-0.70 [-1.68]*	1.70 [4.08]*	-0.48 [-1.17]	1.47 [3.65]***	-0.24 [-0.67]	1.24 [3.52]***	0.07 [0.37]	0.93 [4.84]***
MOM(12)	-0.61 [-1.95]*	1.61 [5.16]***	-0.41 [-1.34]	1.41 [4.62]***	-0.20 [-0.76]	1.2019 [4.52]***	0.04 [0.18]	0.96 [4.64]***
VOL(1, 9)	16.11 [0.20]	-15.10 [-0.18]	10.06 [0.18]	-9.06 [-0.16]	2.95 [0.28]	-1.95 [-0.19]	-0.36 [-0.08]	1.36 [0.31]
VOL(1, 12)	-8.27 [-0.31]	9.27 [0.35]	-4.64 [-0.30]	5.64 [0.37]	-2.06 [-0.26]	3.06 [0.39]	0.42 [0.38]	0.58 [0.53]
VOL(2, 9)	-2.14 [-1.13]	3.14 [1.65]*	-1.27 [-0.94]	2.27 [1.68]*	-0.59 [-0.67]	1.59 [1.80]	0.03 [0.07]	0.97 [2.69]***
VOL(2, 12)	-1.44 [-1.41]	2.44 [2.38]***	-0.88 [-1.10]	1.88 [2.35]***	-0.40 [-0.72]	1.40 [2.50]***	0.06 [01.9]	0.94 [3.26]***
VOL(3, 9)	-1.09 [-1.71]*	2.09 [3.28]***	-0.70 [-1.27]	1.70 [3.09]***	-0.31 [-0.79]	1.31 [3.34]***	0.05 [0.26]	0.95 [4.573]***
VOL(3, 12)	-0.85 [-1.89]*	1.85 [4.11]***	-0.54 [-1.33]	1.54 [3.79]***	-0.24 [-0.75]	1.24 [3.88]***	0.08 [0.40]	0.92 [4.85]***

This table reports the fraction of the four-firm characteristics that explain the cross-sectional variation captured by the 14 technical indicators. We apply the variance decomposition method of Hou and Loh (2016) to decompose each of the 14 technical indicators into the explained component and residual component. First, we apply the univariate cross-sectional regression as follow:

$$r_{i,t} = \alpha_{i,t} + \theta_{j,t} x_{i,j,t-1} + \varepsilon_{i,t},$$

where $r_{i,t}$ ($x_{i,j,t-1}$) is the equity return (jth technical indicator) of stock i at month t. Second, we exam the relationship between the each technical indicator and each of the four momentum factors:

$$x_{i,j,t-1} = a_{j,m,t-1} + \eta_{j,m,t-1} V_{i,m,t-1} + \epsilon_{i,j,m,t-1} \quad \text{for } m = \text{MOM3, MOM6, MOM9, MOM12},$$

Third, we decompose $x_{i,j,t-1}$ into the explained component and residual component based on the regression coefficients $\eta_{j,m,t-1}$:

$$\theta_{j,m,t} = \frac{Cov(r_{i,t},\ x_{i,j,t-1})}{Var(x_{i,j,t-1})} = \frac{Cov(r_{i,t},\ \eta_{j,m,t-1} V_{i,m,t-1})}{Var(x_{i,j,t-1})} + \frac{Cov(r_{i,t},\ a_{j,m,t-1} + \epsilon_{i,j,m,t-1})}{Var(x_{i,j,t-1})} = \theta^C_{j,m,t} + \theta^R_{j,m,t},$$

where $\eta_{j,m,t-1} V_{i,m,t-1}$ ($a_{j,m,t-1} + \epsilon_{i,j,m,t-1}$) is the related (residual) component of $x_{i,j,t-1}$. The 'E(C/Y)' ('E(R/Y)') column corresponds to the explained (residual) fraction $\frac{\theta^C_{j,m,t}}{\theta_{j,m,t}}$ ($\frac{\theta^R_{j,m,t}}{\theta_{j,m,t}}$). MOM3 (MOM6, MOM9, and MOM12) is the momentum calculated by the cumulative returns over past 3 (6, 9, and 12) months. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We further investigate the well-documented four characteristics: market capitalization, book-to-market ratio, investment, and operating profit. Table 3.6 shows that none of the four candidate variables explain the cross-sectional determinant obtained by the technical indicators. The explained fractions attributable to the book-to-market ration, size, and investment are either insignificantly negative or negligibly small, and statistically insignificant. Panel D reports a similar result that operating profit is uncorrelated with the cross-sectional stock returns determinant provided by the technical indicators. Therefore, we conclude that the well-known four factors have an insignificant contribution to all the 14 technical variables in explaining cross-sectional stock expected returns.

Table 3.7. Decomposition: BM, capitalization, investment, and operating profit

Indicators	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)	E(C/Y)	E(R/Y)
	Panel A: BM		Panel B: Size		Panel C: Investment		Panel D: Operating Profit	
MA(1, 9)	-0.94 [-0.25]	1.94 [0.52]	-0.01[-0.55]	1.01 [58.80]***	-0.04 [-0.70]	1.04 [20.26]***	0.00 [0.00]	1.00 [29.29]***
MA(1, 12)	-0.39 [-0.38]	1.39 [1.35]	-0.01 [-0.41]	1.01 [58.97]***	-0.01 [-0.47]	1.01 [43.72]***	0.00 [0.16]	1.00 [47.88]***
MA(2, 9)	-0.29 [-0.46]	1.29 [2.05]**	0.00 [0.10]	1.00 [63.77]***	-0.01 [-0.72]	1.01 [56.39]***	0.00 [0.19]	1.00 [75.36]***
MA(2, 12)	-0.20 [-0.50]	1.20 [3.02]***	0.00 [0.08]	1.00 [69.40]***	-0.00 [-0.30]	1.00 [82.08]***	0.00 [0.24]	1.00 [81.71]***
MA(3, 9)	-0.34 [-0.52]	1.34 [2.04]**	0.03 [1.14]	0.97 [44.14]***	-0.01 [-0.61]	1.01 [51.91]***	0.01 [0.65]	0.99 [84.71]***
MA(3, 12)	-0.26 [-0.59]	1.26 [2.89]***	0.01 [0.56]	0.99 [70.12]***	-0.00 [-0.05]	1.00 [94.52]***	0.01 [0.88]	0.99 [120.91]***
MOM(9)	-0.34 [-0.52]	1.34 [2.02]**	-0.03 [-0.85]	1.03 [31.42]***	-0.01 [-0.54]	1.01 [44.49]***	0.00 [0.24]	1.00 [57.76]***
MOM(12)	-0.03 [-0.21]	1.03 [6.95]***	-0.00 [-0.16]	1.00 [45.36]***	-0.00 [-0.22]	1.00 [62.99]***	0.03 [1.24]	0.97 [35.22]***
VOL(1, 9)	0.49 [-0.90]	0.50 [0.93]	0.88 [0.08]	0.12 [0.01]	0.16 [0.52]	0.84 [2.73]***	-0.01 [-0.13]	1.01 [13.10]***
VOL(1, 12)	1.13 [0.41]	-0.13 [-0.05]	-0.25 [-0.37]	1.25 [1.82]*	-0.50 [-0.11]	1.50 [0.33]	0.53 [0.07]	0.47 [0.06]
VOL(2, 9)	-0.76 [-0.27]	1.76 [0.63]	-0.01 [-0.25]	1.01 [20.67]***	-0.07 [-0.74]	1.07 [11.92]***	0.03 [0.78]	0.97 [22.63]***
VOL(2, 12)	-0.40 [-0.43]	1.40 [1.51]	-0.03 [-0.85]	1.03 [25.36]***	-0.03 [-0.83]	1.03 [27.38]***	0.03 [1.07]	0.97 [37.93]***
VOL(3, 9)	-0.79 [-0.34]	1.79 [0.76]	0.001 [0.28]	0.99 [33.08]***	-0.02 [-0.83]	1.02 [36.13]***	-0.00 [-0.07]	1.00 [46.03]***
VOL(3, 12)	-0.54 [-0.48]	1.54 [1.37]	-0.01 [-0.24]	1.01 [40.87]***	-0.01 [-0.54]	1.01 [56.10]***	0.01 [0.44]	0.99 [61.93]***

This table reports the fraction of the four-firm characteristics: BM, Size, Investment (INV), and operating profit (OP) that explain the cross-sectional variation in expected returns captured by the 14 technical indicators. We apply the variance decomposition method of Hou and Loh (2016) to decompose each of the 14 technical indicators into the explained component. First, we apply the univariate cross-sectional regression as follow:

$$r_{i,t} = \alpha_{i,t} + \theta_{j,t} x_{i,j,t-1} + \varepsilon_{i,t},$$

where $r_{i,t}$ ($x_{i,j,t-1}$) is the equity return (*j*th technical indicator) of stock *i* at month *t*. Second, we exam the relationship between the technical indicator and the four momentums:

$$x_{i,j,t-1} = a_{j,h,t-1} + \eta_{j,h,t-1} V_{i,h,t-1} + \epsilon_{i,j,h,t-1} \quad \text{for } h = \text{BM, Size, INV, OP},$$

Third, we decompose $x_{i,j,t-1}$ into the explained component $\theta^{C}_{h,t}$ and residual component $\theta^{R}_{j,h,t}$ based on the regression coefficients $\eta_{j,h,t-1}$:

$$\theta_{j,h,t} = \frac{Cov(r_{i,t},\ x_{i,j,t-1})}{Var(x_{i,j,t-1})} = \frac{Cov(r_{i,t},\ \eta_{j,h,t-1} V_{i,h,t-1})}{Var(x_{i,j,t-1})} + \frac{Cov(r_{i,t},\ a_{j,h,t-1} + \epsilon_{i,j,h,t-1})}{Var(x_{i,j,t-1})} = \theta^{C}_{j,h,t} + \theta^{R}_{j,h,t},$$

where $\eta_{j,h,t-1} V_{i,h,t-1}$ ($a_{j,h,t-1} + \epsilon_{i,j,h,t-1}$) is the related (residual) component of $x_{i,j,t-1}$. The 'E(C/Y)' ('E(R/Y)') column corresponds to the explained (residual) fraction $\frac{\bar{\theta}^{C}_{j,h,t}}{\bar{\theta}_{j,h,t}}$($\frac{\bar{\theta}^{R}_{j,h,t}}{\bar{\theta}_{j,h,t}}$). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

3.6. Conclusion

We apply 14 technical indicators into the smoothed OLS model to estimate individual stock expected returns in the cross-section, using the Fama French three-factor model and the historical average as benchmarks. Our results show that technical indicators generate lower estimation error than the Fama French three-factor model and exhibit statistically significant out-of-sample explanatory power in determining cross-sectional equity expected returns, and the result is significant over time. The traditional time-series out-of-sample R^2_{TSOS} and the cross-sectional out-of-sample R^2_{CSOS} defined by Han, He, Rapach, and Zhou (2020) are positive and significant. Moreover, we measure the economic value of the cross-sectional model by constructing the value- and equal-weighted long-short portfolios based on the estimated returns of the SOLS model. We find that both the value- and equal-weighted long-short portfolios generate a sizable monthly profit, much higher than the simple market portfolio returns. Lastly, we show that the four well-known determinants of cross-sectional stock returns (momentum, market capitalization, book-to-market ratio, operating profit, and investment) fail to explain the cross-sectional determinant captured by the technical indicators.

Although technical indicators have been well-applied in the time-series setting (LeBaron, 1999; Neely, 2002) and numerous studies give explanation on the theoretical aspects (Treynor and Ferguson, 1985; Brown and Jennings, 1989), their ability on explaining cross-sectional stock returns receive much less attention. Given the fact that technical analysis is widely used by practitioners in the trading (Schwager, 1993; Lo and Hasanhodzic, 2010) and growing number of empirical studies supporting the predictive power of technical indicators (Han, Yan, and Zhou, 2013; Neely, Rapach, Tu, and Zhou, 2014), it important to fill the gap between technical analysis and more traditional asset pricing models. Exploring the relationship between the technical indicators and the cross-sectional stock returns help to improving our understanding of the economic forces that drive the equity risk premium and cross-section of expected asset returns. And our results also show that technical indicators provide additional explanatory information beyond the conventional well-documented cross-sectional determinants.

CHAPTER FOUR: Enduring Momentum

The previous two essays have analyzed the predictive ability of aggregate macroeconomic variables and technical indicators in predicting the time-series individual stock returns and the explanatory power of individual technical indicators in explaining the cross-sectional expected stock returns. Technical indicators are mainly constructed based on information from past prices, and the conventional investment strategy only relies on the magnitude of past returns. The following part of this thesis contribute to utilizing additional information from firm characteristics to improve the profit of conventional price momentum.

4.1. Introduction

The price momentum strategy, constructed based on past prices alone, is one of the most puzzling anomalies in asset-pricing research (Fama and French, 1998). Numerous studies attempt to explain this phenomenon. Some find that certain specific firm attributes and fundamentals provide essential information to explain this anomaly, enhancing traditional price momentum profits (Sagi and Seasholes, 2007; Huang et al., 2019). We contribute to the literature by using a compressive set of firm characteristics to estimate the enduring momentum probabilities of past winners and losers to continue to be future winners and losers and construct an enhanced enduring momentum strategy.

Price momentum that relies only on past price information receive a lot of attention from literature after Jegadeesh and Titman raised it in 1993. Many previous studies document that momentum returns are higher for stocks with specific characteristics, such as higher market-to-book ratios (Daniel and Titman, 1999), smaller size (Hong et al., 2002), and higher analyst forecast dispersion (Zhang, 2006), producing higher momentum profits. Sagi and Seasholes (2007) highlight that not all firms exhibit momentum, understanding future expected returns based on past returns and observable firm-specific attributes helps create enhanced momentum strategies. Huang, Zhang, Zhou, and Zhu (2019) find the firm fundamental play an important role in driving the stock returns, which help to improve the price momentum.

Our duration analysis results for the price momentum suggest that the average duration of the price-determined past winners or losers to be future winners and losers over the six-month holding period is two months. In addition, only a small proportion of past winners (6.46%) and losers (5.60%) remained in their positions throughout the next six-month investment period. This suggests that there is additional information beyond the magnitude of the past returns, and an enhanced or enduring momentum strategy would demand additional information beyond past performances. Therefore, this paper contributes to adding information from firm characteristics to the winners and losers on the price momentum that utilize information from past price only.

In estimating the enduring probability of each winner and loser over time, we apply the survival analysis with the Cox (1972) proportional hazards (PH) model, well-documented in the bankruptcy analysis (Shumway, 2001; Chava and Jarrow, 2004) and corporate default studies (Duffie et al., 2007). In a hazard model, the winner/loser firm's enduring probability changes over time, and its duration is a function of its latest firm characteristic data. The discrete-time Cox PH model explicitly accounts for the follow-up time and automatically adjusts for the period in estimating the probability. Compared to the logistic regression model with the same available follow-up data, the Cox PH model generates stronger statistical power (Cuzick, 1982; Annesi et al., 1989).

We contribute to the literature in the following four ways. First, we develop a Cox PH model that utilizes information from 37 firm characteristics to estimate the probability for each winner or loser at the end of each month t to continue as a winner or loser over the next six-month investment period (t + 1 to t + 6). We refer to this estimated probability as the enduring momentum probability. However, in this study, evaluating the survival time for each winner or loser is different from traditional survival analysis. The critical difference is that we utilize discrete enduring information to evaluate the duration, whereas the traditional survival analysis calculates the continuous survival time. For example, in the survival analysis, each subject i is assigned a "survival" time T_i ($t <= T_i <= T$).

When we evaluate the duration over which price-determined past winners or losers continue to be future winners or losers over the investment period after formation month t, it is challenging to obtain a continuous survival time as in a conventional survival analysis sample. This is because the "survival" time can only occur at randomly discrete points in time for a winner or loser (h = 1, 2, 3, 4, 5, or 6 over the six-month holding period (t + 1 to t + 6)). Therefore, we define survival time or the length of follow-up by counting the total months each winner or loser stays a winner or loser over the six-month holding period and call it "enduring" time. Then, we estimate the enduring probability for all the price momentum winners or losers to be future winners or losers over the following six-month holding period ($M + 1$ to $M + 6$) by utilizing the survival time information for all the winners or losers formed at the end of each month m over the past sixty-month ($M - 60$ to $M - 6$)[12].

We find that the enduring momentum probabilities estimated by the Cox PH model for winners and losers are significantly related to the persistence of stock returns. The higher enduring momentum probabilities of winner and loser firms have stronger persistence on expected returns than lower ones. Moreover, we show that the enduring momentum probability plays a vital role in predicting cross-sectional stock returns. The enduring momentum probabilities for the winners (losers) are significantly positively (negatively) related to future returns, which cannot be explained by the price momentum signals evaluated by the past six-month cumulative returns of winners (losers).

Second, we contribute to the literature by constructing an enhanced enduring momentum strategy by filtering winners and losers of price momentum based on their estimated enduring momentum probabilities. Instead of investing in all past winners and losers of price momentum, we buy the top ten past winners and sell the top ten past losers with the highest estimated enduring probabilities, holding this position for six months. The long-short portfolio of our enduring momentum strategy generates an average monthly return of 2.19%, almost double that of the traditional price momentum portfolio. In addition, we find that the well-known capital asset pricing model (CAPM),

[12] To avoid the look-ahead bias, we form the price momentum for winners and losers until month M - 6 of each sixty-month rolling window. For all the winners and losers created at the end of month M - 6, we count their total survival months over the following six months $M - 5$ to M.

three-factor, and Carhart four-factor models cannot explain this abnormality. The Sharpe ratio and risk-adjusted returns from the enduring momentum strategy are significantly higher than those from the price momentum strategy.

Third, we explore whether the abnormal returns of the enduring momentum strategy vary with seasonality or decay over time. Jegadeesh and Titman (1993) find that their momentum strategy shows a solid negative January return, and this phenomenon is also evidenced in Chordia and Shivakumar's (2005) earnings momentum. However, we find that our enduring momentum strategy consistently generates positive profits during January and non-January periods and is higher than the profit of the price momentum strategy. Moreover, our results suggest that the long-short portfolio profit does not decay with time and produces significant positive returns in all subsamples.

Fourth, this study examines whether the limits of arbitrage drive the profits of the enduring momentum strategy. Previous studies evidence that characteristic screens leading to enhanced momentum profits support limits-to-arbitrage explanations for momentum. For example, Bandarchuk and Hilscher (2012) argue that well-documented characteristics, such as size and illiquidity (also the commonly used proxies for limits of arbitrage) enhance momentum profit because they have more extreme returns, leading to higher momentum profits. Therefore, we question whether our enduring momentum profit disappears after adjusting for the limits of the arbitrage effect. We find that the earnings of the enduring momentum strategy remain positive after excluding 20% of firms with the smallest (largest) size, highest (lowest) volatility, or lowest (highest) liquidity, indicating that limits of arbitrage do not drive such profits.

The remainder of this paper is organized as follows. Section 2 provides the data and methodology for estimating the enduring momentum probability and constructing an enduring momentum strategy. Section 3 presents the empirical results, and Section 4 concludes the paper.

4.2. Key Literature

In the early study of Ball and Brown (1968), they find that the stock market usually reacts in the same direction as the sign of an earnings surprise drifts in that direction for several months. Jegadeesh and Titman (1993) introduce a momentum strategy that buys high-performing individual stocks and sells low-performing individual stocks based on their previous 3-to-12-month returns, which generates a significant abnormal return. In 2001, they confirm and extend this momentum strategy based on past prices. Thereafter, many studies have implemented this strategy in the U.S. market and globally (Liu, Warner, and Zhang, 2006; Avramov, Chordia, Jostova, and Philipov, 2007; Doukas and McKnight, 2005; Antoniou, Lam, and Paudyal, 2007; Galariotis, 2010). In a more relatively recent study, Moskowitz, Ooi, and Pedersen (2012) find that the momentum strategy also exists in time-series which provides an alternative approach for selecting stocks based on their past performance.

Considerable literature aims to explain the influence of the momentum effect, and the explanations are broadly categorized into three camps. The first group supports the irrational behavior theory, in which investors react differently to price-related information. For instance, Barberis, Shleifer, and Vishny (1998) indicate that stock prices react to firm-specific information with delay and return to subsequent mean reversion after acknowledging the deviation from fundamentals. In addition, behavioral deficiencies claim that investors may also suffer from biased self-attribution and overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998), individualism (Chui, Titman, and Wei, 2010), and bounded rationality (Hong and Stein, 1999). The second group advocates rational explanations and the notion of market efficiency and argues that the abnormal momentum anomaly is the compensation of the risk or the trading cost, such as risk adjustment procedure misspecification (Wang and Wu, 2011), time-varying unsystematic risk (Li, Miffre, Brooks. And O'Sullivan, 2008), and transaction costs (Lesmond, Ogden, Trzcinka, 1999).

Moreover, many variables have a significant relationship between momentum abnormal returns and different firm-specific variables, which contributes to improving momentum benefits. For example, Asem (2009) finds a significant relationship between dividend payment and momentum profit and provides evidence that the profits of the price momentum strategy are higher among dividend-paying firms than those that are not paid. Lee and Swaminathan (2000) show that past trading volume provides valuable information in predicting both the magnitude and persistence of price momentum, and high-volume stocks are evidence of earning higher average returns than low-volume firms. Chordia and Shivakumar (2002) find that momentum profits can be explained by a set of lagged macroeconomic variables, and the momentum profits disappear after adjusting their predictability based on these macroeconomic variables.

In addition to the stock market, the momentum effect can also be found in other asset markets. For example, Moskowitz and Grinblatt (1999) construct an industry momentum strategy that produces higher profits than individual stock momentum strategies. Furthermore, the literature finds momentum evidence from the international market. After investigating 12 European stock markets, Rouwenhorst (1998) finds that a six-month momentum strategy generates an excess return of 1% per month, and the results are robust after adjusting for risk and firm size. Hou and McKnight (2004) present significant momentum profit in the Canada market, while Drew, Veeraraghavan, and Ye (2007) report positive and significant momentum returns in the Australian stock market. Gunasekarage and Kot (2007) provide evidence of momentum in the New Zealand market. Besides, some Asian stock markets, such as Hong Kong (Cheng and Wu, 2010), Taiwan (Du, Huang, and Liao, 2009), and some Pacific Basin stock markets (Hameed and Kusnadi, 2002) are also evidenced momentum effect.

4.3. Data and Methodology

4.3.1. Data

We collect daily returns for all common stocks on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and Nasdaq from the Center for Research in Security Prices (CRSP) database. The monthly returns of all the individual firms used to construct the six-month/six-month price momentum strategy are obtained by compounding their daily returns, and we exclude stocks with share prices less than $1 at the beginning of the holding month. In addition, we obtained data from the Compustat database and follow Green et al. (2017)[13] to construct 102 firm characteristics. Green et al. (2017) argue that data from January 1980 become robustly available. Thus, our analysis starts in January 1980 and ends in December 2018, covering 38 years.

To maximize the predictive ability of firm characteristics and ensure sufficient data for the Cox PH model to calculate the enduring momentum probability, we retain those firm characteristics with missing data of less than 5% over the entire sample period. In addition, we exclude all momentum variables to avoid the momentum effect in the construction of the enduring momentum strategy. After these screening criteria, 37 firm characteristics are remained, and we provide a complete description in Appendix 1. Finally, we collect the four Fama-French and Carhart factors (MKT, BM, HML, and MOM)[14] from Ken French's data library.

4.3.2. Methodology

4.3.2.1 Enduring momentum probability and enduring momentum strategy

This section introduces the terminology common to enduring momentum analysis and discusses the estimation of enduring momentum probability by applying the Cox PH model. It also introduces the difference between the enduring momentum and survival probability and describes how we use the estimated enduring momentum probability to construct the enduring momentum strategy. Before using the Cox PH

[13] Much appreciate Jeremiah Green providing the SAS code on his webpage https://sites.google.com/site/jeremiahrgreenacctg/home.

[14] MKT: market excess return; SMB is the return of small-capitalization minus the big-capitalization; HML is the return of high book-to-market value minus the return of low book-to-market value; WML is the return of winners minus the return of losers.

model to estimate the enduring probability of winners and losers of traditional price momentum, we first follow Jegadeesh and Titman (1993) to select winners and losers. At the end of each month *t*, we rank all the firms into ten equally weighted portfolios in descending order based on their past six-month returns, "winners" ("losers") are firms in the top (bottom) decile portfolio with the best (worst) past performance. We then utilize information from 37 firm characteristics in the Cox PH model to estimate the enduring probability for each winner/loser to continue as a winner/loser over the following six-month holding period.

In the Cox PH model, most survival analysis samples on the *i*th subject range from time t = 1 to t = T, and each subject that fails during the sample period is assigned a "survive" time, T_i. However, the winners or losers formed at the end of month t to keep performing as further winners or losers can only occur at discrete points in time, h = 1, 2, 3, 4, 5, or 6 months over the six-month holding period (t + 1 to t + 6). In this study, we define the "enduring" time as the total number of months for each winner/loser i to be a future winner/loser over the next six-month investment period. For example, firm i is identified as a winner at the end of formation month t. Over its next six-month holding period (t + 1 to t + 6), we observe it perform as a winner again in month (t + 2), month (t + 4), and month (t + 6), then we say the enduring time N_i^W for this winner firm i is 3. The enduring time for the loser is denoted as N_i^L, estimated similarly.

Estimating the enduring probability for each winner and loser at the end of month M, we use the enduring time information for all winners and losers that formed over the past 60 months (M – 60, M) in the standard Cox PH model. Specifically, at the end of each month t from M – 60 to M - 6[15], we count the total number of months or the enduring time $N_i^W(N_i^L)$ for each winner (loser) i to stay in the top (bottom) decile portfolio over the following six-month holding period (t + 1 to t + 6), where $t+6 \leq M-6$. Subsequently, at the end of each rolling window M, we utilize the above enduring information to estimate the probability of the enduring months for each winner/loser over the following six-month holding period (M + 1 to M + 6) by the survival function, $S(\tau|X) = Prob(T \geq \tau|X)$. τ is the total enduring months, ranging from 0 to 6, and X represents a set of observable explanatory variables at the end of month M. We use the 37 firm characteristics as X in this study. And we define this probability as the enduring momentum probability.

The enduring behavior can be described using the hazard function, describing the relative likelihood of the winner or loser exiting the top or bottom decile group based on τ times that they have survived in the top or bottom group:

$$\lambda(\tau|X) = \lim_{\Delta\tau \to 0} \frac{P(\tau \leq T \leq \tau + \Delta\tau | T \geq \tau, X, \beta)}{\Delta\tau}$$
$$= \frac{-dlogS(\tau|X)}{d\tau} = \frac{f(\tau|X)}{S(\tau|X)} = \lambda_0(\tau)\exp(\beta'X), \qquad (4.1)$$

where $f(\tau|X)$ is the density function associated with the distribution of survival

[15] Our regression data exclude the last six months from each rolling window to avoid the look-ahead bias. For example, the first rolling window spans from January 1980 to December 1984, and the first date to estimate the enduring momentum probability is December 1984. We get the "enduring time" for each firm that stays in the winner and loser groups during the six-month holding period at the end of each month from July 1980 to Jun 1984. The last month to count the "enduring time" over the first rolling window is Jun 1984.

duration, $\lambda_0(\tau)$ is the baseline hazard function with all covariates equal to zero, and β is a vector of the parameters. The survival function $S(\tau|X) = Prob(T \geq \tau|X)$, is related to the hazard by

$$S(\tau|X) = exp\left(-\int_0^{\tau} \lambda(u|X)du\right) = exp^{\left(-\int_0^{\tau} \lambda_0(u) exp^{\beta' X} du\right)},$$

$$= exp^{(-\Lambda_0(\tau)\exp(\beta' X))} = S_0(\tau)^{\exp(\beta' X)}, \tag{4.2}$$

where $\Lambda_0(\tau) = \int_0^{\tau} \lambda_0(u)du$ represents the baseline cumulative hazard function at time τ, and $S_0(\tau) = \exp(-\Lambda_0(\tau))$. Let x^* denote a particular value of *X* at the end of rolling window *M*. The estimated enduring momentum probability is defined by substituting estimators for the unknown quantities as:

$$\hat{S}(\tau|x^*) = exp^{(-\hat{\Lambda}_0(\tau)\exp(\hat{\beta}' X))}, \tag{4.3}$$

At the end of each rolling window in month *M*, we obtain seven estimated enduring momentum probabilities for each winner or loser to stay in the corresponding group during the six-month holding period (*M* + 1 to *M* + 6), as τ ranges from one to six. For example, $\hat{S}_{W/L}(6)$ $(\tau = 6)$ represents the estimated enduring probability for each winner (W) or loser (L) to remain so throughout the six-month holding period over months *M* + 1 to *M* + 6. Unlike the price momentum strategy to hold and sell all past winners and losers, we construct the enduring momentum portfolio by buying and selling the top ten winner and loser firms with the highest estimated enduring probability $\hat{S}_W(6)$ and $\hat{S}_L(6)$, respectively, holding this position for six months.

4.3.2.2 Autoregression regression

Sagi and Seasholes (2007) claim that some specific firm attributes (revenues, costs, and real options) restrict winners and losers and those restricted winners and losers have more persistent expected returns. This section tests whether the enduring momentum probability is related to the persistence of stock returns. We first run the autoregression with a one-month lag (AR (1)) for each firm based on a five-year rolling window:

$$r_{i,t-60:t} = a_{i,t} + \rho_{i,t} r_{i,t-61:t-1} + e_{i,t}, \tag{4.4}$$

where $r_{i,t-60:t}$ ($r_{i,t-61:t-1}$) is the stock return of stock i from month t – 60 to t (t – 61 to t – 1). After obtaining the slope $\rho_{i,t}$ (the proxy of stock return persistency of each stock), we determine the relationship between the enduring momentum probability and the persistence of stock returns using the multiple cross-sectional regression over time as follows:

$$\rho_{h,t} = \alpha_{h,t} + \beta_{h,t} EP_{h,t-1} + \varepsilon_{h,t}, \tag{4.5}$$

where $EP_{h,t-1}$ represents the enduring probabilities for the winner (h = W) or loser (h = L) firms, estimated at the end of month t – 1. Subsequently, we calculate the average value of all estimated coefficients $\beta_{h,t}$ and its corresponding *t-value*.

4.3.2.3 Logit regression

We further compare the performance of the estimated enduring momentum probability, and the price momentum signals (past six-month cumulative returns) in determining future winners or losers over the six-month holding period using the following panel logit regression[16]:

$$Y_{h,t} = a_h^k + \gamma_h^k x_{h,t}^k + \epsilon_{h,t}^k, \tag{4.6}$$

where $Y_{h,t}$ is a dummy variable equal to one for the winner (h = W) or loser (h = L) firm of price momentum formed at the end of month t to keep performing as a winner (h = W) or loser (h = L) in any month of the following six-month holding period (t + 1 to month t + 6) and zero otherwise. $x_{h,t}^k$ is the estimated enduring momentum probability (k = EP) for the winners (h = W) and losers (h = L) or the cumulative returns (k = MOM) for the winners (h = W) and losers (h = L) over the past six-month period (t – 6 to t – 1). We further explore the explanatory ability of the enduring momentum probability after controlling for the price momentum signal:

$$Y_{h,t} = a_h + \gamma_h^{SP} EP_{h,t} + \gamma_h^{MOM} MOM_{h,t} + \epsilon_{h,t}, \tag{4.7}$$

where $Y_{h,t}$ is the same dummy variable as in Equation (6), representing the appearance signals of the winners or losers. $MOM_{h,t}$ is the cumulative return of winners (h = W)

[16] We perform the OLS regression by following the same steps of logit regression as a comparison.

or losers (h = L) over the past six months (t – 6 to t), defined as the price momentum signal. $EP_{h,t}$ is the estimated enduring momentum probability for the winner (h = W) or loser (h = L) firms to stay winners or losers over the next six-month holding period.

4.3.2.4 Decomposition analysis

We compare the predictive ability of the enduring momentum probability and momentum signal (past six-month cumulative returns) in forecasting future returns using the following cross-sectional regressions:

$$r_{w,t+1} = a_w^k + \phi_w^k x_{w,t}^k + \epsilon_{w,t}^k, \tag{4.8}$$

where $r_{w,t+1}$ is the stock returns for the winner (w = W) or loser (w = L) firms in month t + 1. $x_{w,t}^k$ is the estimated enduring momentum probability (k = EP) for the winners (w = W) or losers (w = L) or their cumulative returns (k = MOM) over the past six-month period (t – 6 to t – 1). We then control for the cumulative return (momentum signal) in the cross-sectional regression of returns on the enduring momentum probability:

$$r_{w,t+1} = a_w^k + \phi_{w,SP} SP_{w,t} + \phi_{w,MOM} MOM_{w,t} + \varepsilon_{w,t+1}, \tag{4.9}$$

where $EP_{w,t}$ is the estimated enduring momentum probability for the winner (w = W) or loser (w = L) firms and $MOM_{w,t}$ represents the past six-month cumulative returns.

However, Hou and Loh (2016) argue that the traditional method of adding competing variables cannot quantify the explanatory fraction of candidate variables. They introduce a decomposition method to comprehensively evaluate the explained fraction of the candidate variables. We follow their method[17] to detect whether the momentum signal (past six-month cumulative returns) can explain the profit captured by the enduring momentum probability. We first explore whether enduring momentum probability affects the predictability of stock returns using the following cross-sectional regression:

$$r_{i,t+1} = \alpha_{m,t} + \eta_{m,t} EP_{m,i,t} + \varepsilon_{m,i,t}, \tag{4.10}$$

where $r_{i,t+1}$ is the equity return of stock i in month $t + 1$. $EP_{m,i,t}$ is the enduring momentum probability for winner (m = W) or loser (m = L) firms estimated in month t. We consider the momentum return as a candidate variable and examine the relationship between the $EP_{m,i,t}$ and the momentum signal (past six-month cumulative returns) as follows:

$$EP_{m,i,t} = a_{m,t} + \zeta_{m,t} MOM_{m,i,t} + \epsilon_{m,i,t}, \tag{4.11}$$

where $MOM_{m,i,t}$ is the momentum signal for stock i from the winners (m = W) or losers (m = L) decile group evaluated by the cumulative returns over the past six months

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[17] The third chapter also applies this covariance decomposition method in examining whether the five popular factors (momentum, size, book-to-market, investment, and profitability) contribute to the cross-sectional explanatory power generated by the 14 technical indicators.

from months t – 6 to t. Subsequently, we decompose $EP_{m,i,t}$ into two orthogonal components based on the estimated coefficients $\eta_{m,t}$ in Equation (10):

$$\eta_{m,t} = \frac{Cov(r_{m,i,t+1}, EP_{m,i,t})}{Var(EP_{m,i,t})},$$
$$= \frac{Cov(r_{m,i,t+1},\ \zeta_{m,t}MOM_{m,i,t})}{Var(x_{i,j,t-1})} + \frac{Cov(r_{m,i,t+1},\ a_{m,t}+\epsilon_{m,i,t})}{Var(x_{i,j,t-1})},$$
$$= \eta^{C}_{m,t} + \eta^{R}_{m,t}, \tag{4.12}$$

where $\zeta_{m,t}MOM_{m,i,t}$ $(a_{m,t} + \epsilon_{m,i,t})$ is the related (residual) component of $EP_{m,i,t}$. Finally, we use $\frac{\eta^{C}_{m,t}}{\eta_{m,t}}$ $(\frac{\eta^{R}_{m,t}}{\eta_{m,t}})$ to calculate the explained (residual) fractions from the momentum signal of winners (m = W) or losers (m = L) by estimating the means and variance of the fractions over the whole regression period as follows:

$$\hat{E}(\frac{\eta^{C}_{m,t}}{\eta_{m,t}}) \approx \frac{\bar{\eta}^{C}_{m,t}}{\bar{\eta}_{m,t}}, \quad \hat{E}(\frac{\eta^{R}_{m,t}}{\eta_{m,t}}) \approx \frac{\bar{\eta}^{R}_{m,t}}{\eta_{m,t}}, \tag{4.13}$$

$$\widehat{Var}(\frac{\eta^{C}_{m,t}}{\eta_{m,t}}) \approx \frac{1}{T}\left(\frac{\bar{\eta}^{C}_{m,t}}{\bar{\eta}_{m,t}}\right)^2 (\frac{\sigma^2_{\eta^{C}_{m,t}}}{\bar{\eta}^{C\,2}_{m,t}} + \frac{\sigma^2_{\eta_{m,t}}}{\bar{\eta}_{m,t}^{2}} - 2\frac{\hat{\rho}_{\eta^{C}_{m,t},\eta_{m,t}}\sigma^2_{\eta^{C}_{m,t}}\sigma^2_{\eta_{m,t}}}{\bar{\eta}^{C}_{m,t}\bar{\eta}_{m,t}}), \tag{4.14}$$

$$\widehat{Var}(\frac{\eta^{R}_{m,t}}{\eta_{m,t}}) \approx \frac{1}{T}\left(\frac{\bar{\eta}^{R}_{m,t}}{\bar{\eta}_{m,t}}\right)^2 (\frac{\sigma^2_{\eta^{R}_{m,t}}}{\bar{\eta}^{R\,2}_{m,t}} + \frac{\sigma^2_{\eta_{m,t}}}{\bar{\eta}_{m,t}^{2}} - 2\frac{\hat{\rho}_{\eta^{R}_{m,t},\eta_{m,t}}\sigma^2_{\eta^{R}_{m,t}}\sigma^2_{\eta_{m,t}}}{\bar{\eta}^{R}_{m,t}\bar{\eta}_{m,t}}), \tag{4.15}$$

and,

$$t_{\frac{\bar{\eta}^{C}_{m,t}}{\bar{\eta}_{m,t}}} = \frac{\frac{\bar{\eta}^{C}_{m,t}}{\bar{\eta}_{m,t}}}{\sigma(\frac{\bar{\eta}^{C}_{m,t}}{\bar{\eta}_{m,t}})}, \quad t_{\frac{\bar{\eta}^{R}_{m,t}}{\bar{\eta}_{m,t}}} = \frac{\frac{\bar{\eta}^{R}_{m,t}}{\bar{\eta}_{m,t}}}{\sigma(\frac{\bar{\eta}^{R}_{m,t}}{\bar{\eta}_{m,t}})}, \tag{4.16}$$

where $t_{\frac{\bar{\eta}^C_{m,t}}{\bar{\eta}_{m,t}}}$ $(t_{\frac{\bar{\eta}^R_{m,t}}{\bar{\eta}_{m,t}}})$ is the *t-value* used to examine whether the explained (residual) fraction is significantly different from zero.

4.4. Empirical Results

4.4.1. Distribution of Enduring Momentum Probability

The construction of the traditional price momentum strategy is based on the assumption that past winners or losers will continue to perform as winners or losers. However, this assumption does not hold for all winners and losers. Therefore, we start our analysis by summarizing the average enduring months and the proportion of past winners and losers to keep performing as future winners and losers during the six-month holding period in Table 1. N in the first column represents the total number of months for all past winners (losers) to keep performing as winners (losers) over the six-month holding period (t + 1 to t + 6). We report the corresponding marginal and cumulative proportions in the second (fourth) and third (fifth) columns. In the second (fourth) column, we can see that only 6.46% (5.60%) of past winners (losers) continue to be future winners (losers) throughout the six-month holding period. In comparison, 26.2% of past winners (losers) will no longer appear in the top (bottom) decile group over the entire investment period. The last two rows of Table 4.1 report the mean and median enduring months, indicating that the average number of enduring months for both winners and losers is two.

Sagi and Seaholes (2007) find that some firm characteristics contribute to the persistence of stock returns, producing enhanced momentum profits. We apply comprehensive firm attributes to the Cox PH model to estimate the enduring momentum probabilities for all the winners and losers of price momentum. Appendix 2 estimates the impact of firm characteristics on the conditional probability of exiting the top and bottom decile group using the proportional hazard in Equation (4.1) and the Cox PH model. As the duration is inversely related to the hazard rate, a positive (negative) coefficient estimate implies a shorter (longer) duration. For example, the estimated coefficients of *age* and *bm* are positive and significant for winner firms in Panel A, indicating that winners with shorter ages and lower book-to-market ratios stay longer in the winner group over the six-month holding period.

Table 4.1. Proportion of past winners (losers) to be future winners (losers)

	Winners		Losers	
N	Marginal	Cumulative	Marginal	Cumulative
0	0.262	0.262	0.253	0.253
1	0.214	0.476	0.216	0.469
2	0.165	0.641	0.168	0.637
3	0.127	0.767	0.132	0.769
4	0.096	0.863	0.100	0.869
5	0.073	0.936	0.075	0.944
6	0.065	1.000	0.056	1.000
Mean	2.06		2.06	
Median	2.00		2.00	

This table reports the proportion and average months for past winners (losers) to be future winners and losers over the six-month investment-holding period. We start by following Jegadeesh and Titman (1993) to define winners (losers) as firms in the top (bottom) decile group with the highest (lowest) past six-month cumulative returns. N in the first column represents the total number of months for all past winners (losers) to keep performing as winners (losers) over the six-month holding period (t + 1 to t + 6). We report the corresponding marginal and cumulative proportions in the second (fourth) and third (fifth) columns. For example, 0.262 in the second column indicates that 26.20% of winners formed at month t fail to continue performing as winners over the six-month holding period (t + 1 to t + 6). Moreover, 0.065 represents that 6.50% of winners will remain winners throughout the six-month holding period (t + 1 to t + 6). The "mean" ("median") row reports the average (median) enduring months, two for winner and loser firms.

Appendix Table A 3.1 reports the summary statistics of the estimated enduring momentum probabilities for all winners and losers. This includes the average, standard deviation, median, maximum, and minimum estimated probabilities of all enduring months. At the end of each month *t*, we estimate the probability of each winner or loser firm continuing as winners or losers for one (two, three, four, five, and six) month (months) over the entire six-month holding period. We then calculate the cross-sectional average, median, standard deviation, maximum, and minimum values of the estimated enduring momentum probabilities for all firms. Finally, we consider the time-series average of each statistic across all months. We can see that the average estimated enduring momentum probability for winners or losers to appear for one (six) month over the six-month holding period is 58.0% (4.70%) or 58.1% (4.50%), higher than the actual enduring momentum proportion for winners or losers in Table 4.1.

4.4.2. Predictability of Enduring Momentum Probability and Momentum Factor

Table 4.2 examines whether the 37 firm characteristics estimated enduring momentum probabilities are related to the persistence of stock returns. Besides, it compares the performance of the enduring momentum probability and momentum returns in detecting future winner and loser firms. We find that the enduring momentum probabilities for winner and loser firms are significantly related to the persistence of stock returns and play a significant role in detecting future winners and losers. However, the momentum signal (past six-month cumulative returns) shows only the predictive ability for winner firms. Panel A of Table 4.2 reports the sensitivity of the return autocorrelation to the change in the estimated enduring momentum probability for winner or loser firms. The positive and significant coefficients in Panel A indicate that the enduring momentum probabilities for winner and loser firms contain predictive information for the persistence of stock returns. A higher enduring momentum probability increases the autocorrelation of individual stock returns.

Panels B and C of Table 4.2 show the predictive performance of enduring momentum probability and the momentum signals (past six-month cumulative returns) of all winners and losers in detecting future winner and loser firms over the six-month holding period by applying the logit and OLS models. The results suggest that the enduring momentum probability predicts winners and losers over the holding period and still has predictive power after controlling the momentum signal. The γ_W^{EP} rows of Panels B and C present the predictive ability of the enduring probability, and we observe that all the estimated coefficients of winners and losers for the logit regression in Panel B and OLS regression in Panel C are positive and significant. The results do not change when we add cumulative returns as a control variable in the last column of Panels B and C.

Table 4.2. Economics content of enduring momentum probability

Panel A: Enduring momentum probability and persistency of stock returns				
		Winners		Losers
	β_{EP}	0.1033		0.3767
	t-value	[5.07]***		[15.76]***
Panel B: Does enduring momentum probability detects future winners/losers? (Logit)				
Winners	γ_W^{EP}	2.7672		0.9904
(145491)	p-value	(<.0001)***		(<.0001)***
	γ_W^{MOM}		0.5284	0.5083
	p-value		(<.0001)***	(<.0001)***
	R^2	0.0702	0.0117	0.0715
Losers	γ_L^{EP}	4.7194		3.5879
(103238)	p-value			(<.0001)***
	γ_L^{MOM}	(<.0001)***	-1.6084	-1.4458
	p-value		(<.0001)***	(<.0001)***
	R^2	0.0267	0.0523	0.0661
Panel C: Does enduring momentum probability detects future winners/losers? (OLS)				
Winners	γ_W^{EP}	0.7004		0.0613
(145491)	t-value	[29.61]***		[19.60]***
	γ_W^{MOM}		0.0662	0.3899
	t-value		[20.91]***	[14.91]***
	R^2	0.0068	0.0243	0.0262
Losers	γ_L^{EP}	1.2444		0.8784
(103238)	t-value	[25.58]***		[20.22]***
	γ_L^{MOM}		-0.4962	-0.4448
	t-value		[-63.53]***	[-54.25]***
	R^2	0.0157	0.0351	0.0425

This table reports the ability for enduring momentum probability in explaining stock returns persistency in Panel A and its capability in detecting future winners/losers in Panel B. Panel A contains the explanatory ability results by the following cross-sectional regression:

$$\rho_{i,t} = \alpha + \beta_{EP} EP_{t-1} + \varepsilon_t,$$

where $\rho_{i,t}$ is the proxy for the persistence of each stock from its autoregression over the past 60 months, EP_{t-1} is the enduring momentum probability for all winners/losers. The positive and significant value of β_{EP} suggests that enduring momentum probability explains the persistence of stock returns. Panel B (C) reports the results of the panel logit (OLS) regression as follows:

$$Y_{h,t} = a_h^k + \gamma_h^k x_{h,t}^k + \epsilon_{h,t}^k,$$

where $Y_{h,t}$ is a dummy variable equal to one for the winner (h = W) or loser (h = L) firms of price momentum to keep performing as winners/losers in any month of the following six-month holding period (t + 1 to t + 6) and zero otherwise. $x_{h,t}^k$ is the estimated enduring momentum probability (k = EP) for the winners (h = W)/losers (h = L) or the cumulative returns (k = MOM) for winners/losers over the past six months (t – 6 to t – 1). We report the regression observations in brackets in the first column. *** indicate statistical significance at the 1% level.

The results for the momentum signal (γ_W^{MOM}) in Panels B and C suggest that only the cumulative returns of the winners play a significant role in detecting future winners. By contrast, the cumulative returns of loser firms fail to detect future losers. In the third column of Panels B and C, we can see that the estimated coefficients γ_L^{MOM} of momentum signals (past six-month returns) are positive and significant for the winners but negative and significant for the losers for both logit and OLS regressions in the fourth column.

We are motivated to enhance the traditional momentum strategy profit using the newly constructed long-short portfolios based on buying and selling the top ten winners and losers with the highest enduring momentum probabilities. In addition, we expect a positive or negative relationship between the enduring momentum probability of winners or losers and future returns, and the conventional momentum signal (past six-month cumulative return) should not explain this predictability. Table 4.3 shows the predictive ability of the enduring momentum probability in forecasting stock returns and investigates whether the momentum signal shares the predictive information captured by the enduring momentum probability.

The results in Panel A suggest that the enduring momentum probabilities of the winners and losers generate significant predictive information for future stock returns. In contrast, only cumulative returns for losers show predictive ability for cross-sectional stock returns. We observe that the estimated coefficient of enduring momentum probability for winner (loser) firms in the third column of Panel A is positive (negative) and significant and remains that way after adding the cumulative returns as a control variable in the last column of Panel A. However, the estimated coefficient for the momentum signal in the fourth column of Panel A is negative and significant for losers but insignificant for winners.

We further explore whether the momentum signal can explain the predictability of stock returns captured by the enduring momentum probability by applying the decomposition method introduced by Hou and Loh (2016) and report the results in Panel B of Table 4.3. We observe that the momentum signal constructed based on past stock returns fails to share the predictive information provided by the enduring probability in forecasting stock returns for winner and loser firms. The magnitude of the explained fraction is small and statistically insignificant for winner firms in the second row of Panel B and significantly negative for loser firms in the fourth row of Panel B.

Table 4.3. Predictive ability comparison

Panel A: OLS regression				
Winners	ϕ_W^{EP}	0.0696		0.0717
		[2.23]**		[2.41]***
	ϕ_W^{MOM}		-0.0004	-0.0018
			[-0.22]	[-1.11]
Losers	ϕ_L^{EP}	-0.2687		-0.3230
		[-8.31]***		[-10.17]***
	ϕ_L^{MOM}		-0.0948	-0.1220
			[-5.73]***	[-7.23]***
Panel B: Decomposition				
	Explain fraction			Residual fraction
Winners	0.0324			0.9676
	[0.32]			[9.61]***
Losers	-0.1322			1.1322
	[-3.13]***			[26.81]***

This table reports the explanatory power of the enduring momentum probability in forecasting future returns and the decomposition results of this explanatory power by the price momentum signal. The second and third column of Panel A examines how enduring momentum probability and momentum signal (past six-month cumulative return) perform in predicting the future returns by the following cross-sectional regression:

$$r_{w,t+1} = a_w^k + \phi_w^k x_{w,t}^k + \epsilon_{w,t}^k,$$

where $r_{w,t+1}$ is the stock return for winner (w = W)/loser (w = L) firms in month t + 1. $x_{w,t}^k$ is the estimated enduring momentum probability (k = EP) for the winners/losers or the cumulative returns (k = MOM) for the winners (w = W)/losers (w = L) over the past six-month period (t – 6 to t – 1). We then control for the cumulative return in the regression of returns on the enduring momentum probability and report the results in the last column of Panel A:

$$r_{w,t+1} = a_w^k + \phi_{w,SP} EP_{w,t} + \phi_{w,MOM} MOM_{w,t} + \varepsilon_{w,t+1},$$

Panel B reports the fractions for the momentum signal and explains the predictability captured by the enduring momentum probability. We follow Hou and Loh (2016) to decompose the $EP_{m,i,t}$ into the explained component and residual component by the candidate variable $MOM_{w,t}$ and report the results in Panel B. *** indicate statistical significance at the 1% level.

4.4.3. Profit of Price Momentum, and Enduring Momentum Strategies

Table 4.4 reports the monthly average returns of portfolios constructed based on the traditional price momentum and our enduring momentum strategy that filter from the price momentum by buying the top ten past winners and selling the top ten past losers with the highest enduring probabilities. The results suggest that the enduring momentum strategy is different from the conventional price momentum strategy and generates a noticeable higher profit than the traditional price momentum strategy. The spread portfolio of the price momentum in the second column yields a 1.12% monthly return. The average monthly return of the portfolios formed based on the enduring momentum strategy in the third column is 2.19% per month[18]. The premium difference between the enduring momentum and the price momentum in the last column shows that our enduring momentum strategy produces a significant 1.07% higher average returns per month than the traditional price momentum strategy.

[18] Moreover, our test shows that the monthly average portfolio returns for buying the top ten firms with the highest past six-month cumulative returns and selling the lowest past six-month cumulative return is 0.51%.

Table 4.4. Price momentum and enduring momentum returns

	Price momentum	Enduring momentum	Difference
Winners	0.0132	0.0138	
	[3.96]***	[2.77]***	
Losers	0.0019	-0.0081	
	[0.39]	[-1.29]	
WML	0.0112	0.0219	0.0107
	[3.20]***	[4.24]***	[2.47]***

This table reports the monthly returns of the investment portfolios formed on the price momentum strategy and enduring momentum strategy. The second column shows the monthly returns for the traditional price momentum portfolios. The third column reports the average monthly returns of the portfolios formed based on the enduring momentum strategy. The last column reports the spread portfolio profit difference between the enduring momentum and the price momentum strategy. *** indicate statistical significance at the 1% level.

4.4.4. Risk-Adjusted Returns and Summary Statistics

Table 4.5 presents the risk-adjusted returns for the price momentum and enduring momentum strategies based on the capital asset pricing model (1964), Fama and French's (1992) three-factor model, and Carhart's (1997) four-factor model. Consistent with the previous study, the enduring momentum strategy results in the second to fourth columns of Table 4.5 suggest that the well-documented factors cannot explain the abnormal returns generated by the enduring momentum strategy. All the alphas of the three asset pricing models are positive and significant at the 1% level.

Similar results are found in the fifth and sixth columns of the portfolios based on the price momentum strategy. However, the risk-adjusted return of the spread portfolio in the last column for the Carhart four-factor model that includes the momentum factor is positive but statistically insignificant, suggesting that the enduring momentum strategy enhances traditional price momentum by filtering past winners and losers. Additionally, the firm characteristics utilized in filtering price momentum winners and losers provide additional information beyond past prices. Moreover, all abnormal portfolio returns based on the enduring momentum strategy are higher than those based on the conventional price momentum strategy. Furthermore, we find that the enduring momentum strategy generates a Sharpe ratio of 19.69%, far exceeding the Sharpe ratio of the price momentum strategy (12.86%). The wild bootstrap procedure[19] generates a *p*-value (0.9), suggesting that the enduring momentum strategy has a significantly higher Sharpe ratio than the price momentum strategy.

[19] The bootstrap procedure is constructed using the following steps: we first randomly select observations with replacement and same sample size from the original monthly portfolio profits of the enduring momentum and price momentum strategies. Second, we use the bootstrapped return of each month to calculate the mean value and standard deviation and get the corresponding Sharpe ratio of each strategy. Third, we calculate the Sharpe ratio difference between the enduring momentum and the price momentum strategies. Lastly, we repeat the above three steps 500 times, which allow us to calculate the distribution of the positive proportion of the Sharpe ratio difference between enduring momentum and the price momentum and evaluate the p-value.

Table 4.5. Risk-adjust returns and summary statistics of long-short portfolio returns

	CAPM	FF3	Carhart4	CAPM	FF3	Carhart4
	Enduring Momentum			Price Momentum		
alpha	0.2570	0.0270	0.0143	0.0143	0.0148	0.0034
	[4.97]***	[5.22]***	[3.38]***	[4.03]**	[4.15]***	[1.49]
MKT	-0.0035	-0.0044	-0.0006	-0.0033	-0.0033	0.0001
	[-3.00]***	[-3.65]***	[-0.57]	[-4.09]***	[-3.99]***	[0.22]
SMB		0.0021	0.0025		-0.0018	-0.0015
		[1.22]	[1.75]*		[-1.48]	[-1.95]*
HML		-0.0040	0.0014		-0.0021	0.0026
		[-2.11]**	[0.87]		[-1.65]*	[3.12]***
MOM			0.0084			0.0075
			[14.87]***			[24.61]***
R^2	0.0217	0.0398	0.3801	0.0396	0.0489	0.6199
N	408	408	408	408	408	408

This table reports the risk-adjusted returns from the CAPM, Fama-French three-factor, and Carhart four-factor models in Panel A and the summary statistics for the long-short portfolio formed by the enduring momentum strategy in Panel B. The last row reports the total number of regression observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.4.5. Seasonal Effect

Jegadeesh and Titman (1993) document the seasonal behavior of the price momentum strategy: loser firms generate significantly higher returns than winner firms in January. McLean and Pontiff (2016) find that anomalies decay over time. Thus, we examine the performance of the enduring momentum and price momentum strategies in the January and non-January periods, report the corresponding results in Panel A of Table 4.6, and explore the performance of the two strategies for the 1985:01 to 1999:12 and 2000:01 to 2018:12 subsamples in Panel B.

We find that the enduring momentum strategy is much less affected by seasonality and shows consistent long-short profits over time than the price momentum strategy. The enduring momentum strategy generates a positive January profit (1.79%), as seen in the second column of Panel A. However, the average monthly profit is negative and significant (-0.50%) for the price momentum strategy in the third column of Panel A. Thus, the profit difference in the last column of Panel A shows that the January profit for the enduring momentum strategy is significantly higher than that for the price momentum strategy. Nevertheless, the non-January gains are positive and significant for both strategies.

Panel B of Table 4.6 shows that the average monthly return of the enduring momentum strategy is 3.21% in the first subsample and 1.63% in the second subsample, and significant at or above the 5% level. However, for the price momentum strategy, the long-short portfolio returns decline from 2.02% in the first subsample to 0.57% in the second subsample. We find no significant evidence for the second subsample. The last column of Panel B shows the profit difference between the two strategies for the two sub-samples. The enduring momentum strategy consistently outperforms the price momentum strategy at the 10% level.

Table 4.6. Seasonal effects and subsample performance

	Enduring momentum	Price momentum	Difference
Panel A: Seasonal effects			
January	0.0179	-0.0050	0.0683
	[0.85]	[2.19]**	[2.93]***
Feb-Dec	0.0238	0.0178	0.0060
	[4.49]***	[5.63]***	[1.56]
Panel B: Subsample periods performance			
1985.01 - 1999.12	0.0321	0.0202	0.0119
	[5.54]***	[6.04]***	[1.94]*
2000.01 - 2018.12	0.0163	0.0057	0.0107
	[2.04]**	[0.97]	[1.92]*

This table reports the average returns for January and non-January periods of the enduring momentum and price momentum strategies in Panel A and portfolio returns of the two strategies for the 1985:01 to 1999:12 and 2000:01 to 2018:12 subsamples in Panel B. We present the results for the enduring momentum in the second column and the results for the price momentum strategy in the third column. We calculate their difference in the last column of each panel. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.4.6. Turnover Ratio and Break-Even Transaction Cost

In many studies, a price momentum portfolio usually has a higher turnover ratio than a market portfolio. This section examines whether high turnover-related transaction costs offset the overperformance of the price momentum and enduring momentum strategies. Following Brandt et al. (2009), we calculate the turnover ratio in month *t* as the summation of the absolute values of the weight changes of all securities in the corresponding portfolio between months $t-1$ and *t*. We report the turnover ratio and breakeven cost for the price momentum and enduring momentum in Table 4.7, showing that the turnover ratio for the winners/losers of the enduring momentum strategy is 1.3101/1.1381[20]and the corresponding breakeven costs for the long-short portfolio is 0.95%.

Although the turnover ratio of the enduring momentum strategy is higher than that of the price momentum strategy (0.7398 and 0.7587), we select the firms in the enduring momentum strategy after double sorting. We only keep the top ten firms with the highest enduring momentum probability from the top and bottom portfolios. Generally, the breakeven costs in the last column of Table 4.7 suggest that it takes 81 and 95 basis points for the price momentum and enduring momentum strategies, respectively, to achieve zero returns. However, Frazzini et al. (2018) find that trading costs are small in real-world trading. The long-short trade faces an average of 8.37 basis

[20] The winners and losers for the enduring momentum in the last row of Table 7 represent the top ten firms we long and short for the investment portfolio, and if we change all the firms in the long (winners) or short (losers) side of the investment portfolio based on the enduring momentum strategy, the turnover will be 200%, and it can explain why the turnover ratio for the winners/losers of the enduring momentum is above 100%.

points market impact and 9.61 basis points implementation shortfall; both are far smaller than the breakeven cost of our enduring momentum strategy.

Table 4.7. Turnover ratios and break-even transaction costs

	Turnover ratios		Break-even costs
Strategies	Winners	Losers	Zero return
Price momentum	0.7398	0.7587	0.0081
Enduring momentum	1.3101	1.1381	0.0095

This table shows the turnover ratios and corresponding breakeven costs for the price momentum and enduring momentum strategies.

4.4.7. Limits of Arbitrage Effect

This subsection examines whether size, Amihud's (2002) illiquidity index, and volatility, the three primary proxies of limits to arbitrage, drive the abnormal return of the enduring momentum strategy. We construct new investment portfolios based on the enduring momentum strategy by excluding 20% of the sample firms with the smallest (largest) size, highest volatility, or lowest liquidity. We then report the results in Table 8. We find that the limits of the arbitrage effect cannot explain the profit generated by the price momentum, and the enduring momentum has a consistently better performance than the price momentum strategy for all groups.

Table 4.8. Limits of arbitrage effects

Strategy	WML	WML
	Panel A: Size effect	
Excluding the 20% smallest stocks		Excluding the 20% largest stocks
Price momentum	0.0119	0.0129
	[3.52]***	[3.60]***
Enduring momentum	0.0197	0.0247
	[4.02]***	[4.83]***
Difference	0.0078	0.0118
	[2.02]**	[2.91]***
	Panel B: Liquidity effect	
Excluding the 20% highest illiquid stocks		Excluding the 20% lowest illiquid stocks
Price momentum	0.0123	0.0125
	[3.49]***	[3.62]***
Enduring momentum	0.0207	0.0241
	[4.19]***	[4.61]***
Difference	0.0084	0.0116
	[2.28]**	[2.86]***
	Panel C: Volatility effect	
Excluding the 20% highest volatile stocks		Excluding the 20% lowest volatile stocks
Price momentum	0.0085	0.0129
	[3.40]***	[3.44]***
Enduring momentum	0.0115	0.0229
	[3.03]***	[4.39]***
Difference	0.0030	0.0099
	[1.02]	[2.45]***

This table reports the enduring momentum and price momentum strategies' average long-short returns after excluding the top/bottom 20% decile of stocks from the size, liquidity, or volatility (the three proxies of limits of arbitrage) sorted sample. Panel A (B and C) reports the long-short portfolio returns for the momentum and enduring momentum strategies after considering the size (liquidity and volatility) effect. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

4.5. Conclusion

This study utilizes the information from 37 firm characteristics in the Cox PH model to estimate the enduring momentum probabilities for all winner and loser firms to continue to be winners and losers over the next investment period. We find that the enduring momentum probability is significantly related to the persistence of stock returns. Moreover, the enduring momentum probability can detect future winners and losers compared to momentum returns and plays an important role in predicting cross-sectional stock returns. Furthermore, the enduring momentum probabilities for winners (losers) exhibit a significantly positive (negative) relationship with future returns, and the price momentum signals (past six-month cumulative returns) cannot explain this relationship.

We then enhance the traditional price momentum strategy by constructing the enduring momentum strategy based on the enduring momentum probabilities. Instead of trading all the firms in the top (winner) and bottom (loser) decile groups formed by the traditional price momentum strategy, we buy and sell the top ten firms with the highest enduring momentum probabilities from the winner and loser groups. We find that the enduring momentum strategy generates significantly higher profits than the price momentum strategy, which cannot be explained by well-documented factor models. Moreover, seasonality cannot affect this profitability, and limits to arbitrage do not drive it.

Jagadeesh and Titman (1993) introduce the price momentum that purely utilizes information from the past price, which received a lot of attention from literature afterwards. Recent literature shows that observable fundamental characteristics help improve the traditional price momentum profit. Sagi and Seasholes (2007) document that firms with high revenue growth volatility, low costs, or valuable growth options generate higher profits than the price momentum. Huang, Zhang, Zhou, and Zhu (2019) find the firm fundamental matter in driving the stock returns, which is important in enhancing the conventional price momentum. This paper builds on this finding and contributes to understanding cross-sectional abnormal returns. Specifically, this essay identifies firm characteristics to provide additional information beyond the magnitude of the past returns that are relevant to the future expected returns. Our estimated results show that getting information from firm characteristics helps to enhance the existing momentum profits, which can be applied in the real trading to improve investors' investment profits.

CHAPTER FIVE: Conclusion

This final chapter concludes the thesis by summarizing the major findings. The implications of this research are also discussed. The limitations of this thesis and future research are discussed at the end of this chapter.

5.1. Summary of Contribution

This dissertation focuses on firm-level individual stock returns predictability analysis based on three essays. The first essay explores the performance of well-documented macroeconomic variables and technical indicators in forecasting individual stock returns and detects whether their predictive abilities change with different limits of arbitrage and economic status. The second essay investigates the explanatory ability of cross-sectional stock returns based on 14 well-known technical indicators and uses the Fama–French three-factor model and the historical mean model as benchmarks. In addition, this study also applies the time-series out-of-sample R^2_{TSOS} and cross-sectional out-of-sample R^2_{CSOS} defined by Han, He, Rapach, and Zhou (2020) to measure the out-of-performance of the technical indicators. The third essay estimate the enduring momentum probabilities for winners and losers and construct a corresponding enduring momentum strategy that filter the winners and losers from traditional price momentum strategy based on their estimated enduring momentum probabilities.

5.2. Major Findings and Implications

5.2.1. Essay One

This essay finds that both macroeconomic variables and technical indicators have a significant predictive ability in forecasting individual stock returns. Considering the limits of arbitrage effect, macroeconomic variables and technical indicators play different, but complementary, prediction roles. Macroeconomic variables exhibit a significant predictive ability for firms with low arbitrage (i.e., large size, liquid, and low volatility). In contrast, technical indicators show stronger predictive power for firms with high limits of arbitrage (i.e., smaller size, low liquid, and high volatility).

Moreover, the first essay further detects individual stock return predictability across different economic states and finds that macroeconomic variables and technical indicators generate stable predictive information over time but are considerably better in recessions. However, macroeconomic variables and technical indicators process different information in forecasting firms with various the effect of limits of arbitrage across different market states. Macroeconomic variables show a higher predictive ability for firms with low limits to arbitrage in the recession, whereas technical predictors consistently show significantly stronger predictive power for firms with high limits of arbitrage.

Overall, the first essay provides three important contributions to the literature on the predictability of stock returns. First, this study enriches the literature by investigating firm-level predictability based on the most documented macroeconomic and technical variables. Second, this study adds to the literature by detecting the limits of arbitrage effects on firm-level predictability. Finally, this essay explores time effects on firm-level predictability using macroeconomic variables and technical indicators.

5.2.2. Essay Two

The second essay concludes that the well-documented 14 firm-level technical indicators in the smoothed OSL model outperform the traditional Fama-French three-factor model and the historical mean model in explaining the cross-sectional stock returns by generating lower estimation errors. In measuring explanatory performance of technical indicators, this essay employs both the cross-sectional out-of-sample R^2_{CSOS} defined by Han, He, Rapach, and Zhou (2020) and the traditional time-series out-of-sample R^2_{TSOS}. The positive and significant time-series out-of-sample R^2_{TSOS} and cross-sectional out-of-sample R^2_{CSOS} indicate that the technical indicators outperform the historical mean model in explaining the cross-sectional expected returns.

Moreover, this study contributes to the literature by measuring the economic value of the cross-sectional SOLS model by constructing value- and equal-weighted long-short portfolios based on the estimated returns of the SOLS model. The results show that both the value- and equal-weighted long-short portfolios generate a sizable monthly profit that is much higher than simple market portfolio returns. Finally, this essay detects whether the four well-known determinants of cross-sectional stock returns (momentum, market capitalization, book-to-market ratio, operating profit, and investment) share explanatory information of the technical indicators. However, the results show that all these most-known determinants fail to explain the cross-sectional determinants captured by technical indicators.

Overall, the second essay makes three important contributions to the literature on the cross-sectional expected stock returns. First, this essay enriches the literature by investigating the explanatory power of technical indicators. Second, this essay adds to the existing literature by detecting whether the five most well-known cross-sectional determinants (momentum, market capitalization, book-to-market ratio, operating profit, and investment) share explanatory information from the 14 individual-level technical indicators.

5.2.3. Essay Three

The last essay utilizes the Cox PH model and 37 firm characteristics to estimate the enduring momentum probabilities for all winner and loser firms to continue being winners and losers over the investment period. The results show that the enduring momentum probability is significantly related to the persistence of stock returns and plays a significant role in detecting appearance signals for both winners and losers. In addition, the estimated enduring momentum probabilities can predict cross-sectional stock returns. Therefore, this essay constructs an enduring momentum strategy by buying (selling) the top ten firms with the highest enduring momentum probabilities from past winners (losers). The profits of the enduring momentum strategy are significantly higher than those of the traditional price momentum strategy, which cannot be explained by well-documented factor models. Moreover, the spread profit of the enduring strategy is not affected by the January effects of the price momentum strategy or limits of arbitrage effects.

Overall, the third essay makes four important contributions to the literature on enhancing the profits of the traditional price momentum strategy. First, this essay utilizes information from 37 firm characteristics in the Cox model to estimate the probabilities for past winners and losers to continue performing as winners and losers over the future six-month holding periods. Second, this essay investigates the relationship between the estimated enduring probabilities with the persistence of future returns and whether this significant relationship can be explained by well-documented momentum returns. Third, this essay constructs an enduring momentum strategy by buying (selling) firms in the past winners (losers) with the highest enduring survival probabilities as winners (losers) over the next six-month holding period. Fourth, this essay explores whether this abnormality can be explained by well-documented factor models, seasonality, and limits of arbitrage.

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Appendices

Appendix 1.1. Construction of Firm-Level Technical Indicators

The construction of the 14 firm-level technical indicators follows the method introduced by Neely, Rapach, Tu, and Zhou (2014), mainly based on three trend-following strategies (moving average, momentum, and volume-based indicators). The first strategy is based on the moving average (MA) rule, which forms the trading signals by comparing the two moving averages with different lengths:

$$B_{i,t} = \begin{cases} 1 & \text{if } \; MA_{i,t}^{s} \geq MA_{i,t}^{l} \\ 0 & \text{if } \; MA_{i,t}^{s} \leq MA_{i,t}^{l} \end{cases}, \tag{A1.1a}$$

$$\text{where } \; MA_{i,t}^{j} = \frac{1}{j}\sum_{h=0}^{j-1} P_{i,t-h}, \quad \text{for} \quad j = s, l, \tag{A1.1b}$$

$P_{i,t-h}$ is the stock price level of stock i in month $t-h$. $j = s$ ($j = l$) represents the length of the short (long) MA, and $s < l$. Thus, the MA indicator with MA lengths of s and l is denoted as MA (s, l). We calculate monthly individual stock trading signals with $s = 1, 2, 3$ and $l = 9, 12$ months. $B_{i,t} = 1$ ($B_{i,t} = 0$) represents a buy (sell) signal when the short moving average $MA_{i,t}^{s}$ is higher (lower) than the long moving average $MA_{i,t}^{l}$.

The second strategy is based on the momentum (MOM) trading rule, which generates the trading signals by comparing the current stock price with its level *n* month periods ago as follows:

$$B_{i,t} = \begin{cases} 1 & \text{if } P_{i,t} \geq P_{i,t-n} \\ 0 & \text{if } P_{i,t} \leq P_{i,t-n} \end{cases}, \tag{A1.2}$$

where $P_{i,t}$ is the current stock price of stock i and $P_{i,t-n}$ is the stock price level n months ago. $B_{i,t} = 1$ ($B_{i,t} = 0$) represents a buy (sell) signal when the current stock price level $P_{i,t}$ is higher (lower) than $P_{i,t-n}$, the price level *n* months ago.

The third strategy is based on the "on-balance" volume rule (e.g., Granville, 1963), which generates the trading signals by evaluating the changes in stock trading volume as follow:

$$B_{i,t} = \begin{cases} 1 & \text{if } MA_{i,t}^{OBV,s} \geq MA_{i,t}^{OBV,l} \\ 0 & \text{if } MA_{i,t}^{OBV,s} \leq MA_{i,t}^{OBV,l} \end{cases}, \tag{A1.3a}$$

where

$$MA_{i,t}^{OBV,k} = \frac{1}{k} \sum_{h=0}^{k-1} OBV_{i,t-h}, \tag{A1.3b}$$

$k = s, l$, and the 'on-balance' volume (OBV) is calculated as follow:

$$OBV_{i,t} = \sum_{m=1}^{t} VOL_{i,m} \times D_{i,m}, \tag{A1.4}$$

where $VOL_{i,m}$ represents a measure of the trading volume during period *m* and $D_{i,m}$ is a dummy variable that equals 1 if $P_{i,m} \geq P_{i,m-1}$, and -1 otherwise. $B_{i,t} = 1$ ($B_{i,t} = 0$)

represents a buy (sell) signal, indicating a strong positive (negative) market trend evaluated by the volume-based strategy, which is generated by the relatively high (low) recent volume in conjunction with an increase (decrease) in the recent price. $k = \mathrm{s}$ ($k = l$) represents the short length of the VOL, $s < l$, and we denote the volume indicator by VOL(s, l). We compute the volume-based trading signals with lengths of $s = 1, 2, 3$ and $l = 9, 12$ months.

Table A.1.1. Univariate estimation results (1951.01 – 2018.12)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Macroeconomic variables					Panel B: Technical variables				
	Market level	Firm-level				Market level	Firm-level		
	Slope coefficient	PS (%)	NS (%)	PS-NS [t-stat]		Slope coefficient	PS (%)	NS (%)	PS-NS [t-stat]
BM	0.54 [0.75]	9.23	2.13	7.09 [5.09]***	MA(1,9)	0.67 [1.78]**	9.16	3.63	5.53 [3.98]***
NTIS	0.66 [0.06]	11.57	5.14	6.42 [4.67]***	MA(1,12)	0.87 [2.22]**	8.73	3.41	5.32 [3.82]***
DP	0.78 [1.98]**	13.48	1.63	11.85 [8.58]***	MA(2,9)	0.70 [1.88]**	7.92	3.44	4.47 [3.21]***
EP	0.43 [0.97]	8.08	2.81	5.27 [3.77]***	MA(2,12)	0.94 [2.42]***	7.71	3.27	4.44 [3.18]***
DE	0.59 [0.93]	6.77	2.67	4.10 [2.93]***	MA(3,9)	0.77 [2.04]**	7.60	3.58	4.02 [2.88]***
TBL	0.11 [1.90]*	15.64	1.80	13.84 [10.09]***	MA(3,12)	0.54 [1.39]	7.52	3.57	3.95 [2.83]***
LTY	0.08 [1.25]	9.52	3.54	5.98 [4.31]***	MOM(9)	0.55 [1.40]	7.03	3.60	3.43 [2.46]***
LTR	0.13 [2.05]**	20.13	1.92	18.21 [13.44]***	MOM(12)	0.58 [1.44]	7.23	3.28	3.95 [2.83]***
TMS	0.20 [1.74]*	16.71	1.34	15.37 [11.22]***	VOL(1,9)	0.68 [1.86]**	6.65	5.19	1.46 [1.05]
DFY	0.16 [0.37]	16.82	1.87	14.95 [10.93]***	VOL(1,12)	0.89 [2.31]**	6.89	5.43	1.45 [1.05]
DFR	0.16 [0.89]	10.65	1.79	8.86 [6.37]***	VOL(2,9)	0.74 [2.02]**	6.23	5.61	0.62 [0.44]
DY	0.84 [2.13]**	18.80	1.02	17.78 [13.04]***	VOL(2,12)	0.74 [1.94]*	6.57	5.75	0.81 [0.59]
INFL	0.10 [0.18]	10.77	3.65	7.12 [5.15]***	VOL(3,9)	0.48 [1.27]	6.12	5.91	0.22 [0.16]
RVOL	7.39 [2.45]***	14.97	1.12	13.85 [10.06]***	VOL(3,12)	0.85 [2.25]**	6.00	5.64	0.36 [0.26]

Note: This table shows the market and firm-level bivariate estimation results respectively based on the following regression,

$$y_{t+1} = \alpha_i + \beta_i x_{j,t} + \varepsilon_{j,t+1},$$

where y_{t+1} is the individual firm log excess return for the firm-level forecast, or the S&P 500 log excess return for the market level estimation; $x_{j,t}$ represents the jth predictor from the documented 14 macroeconomic variables or 14 technical predictors. We report the collected market-level bivariate predictive results for macroeconomic and technical indicators from Neely et al. (2014) in the second column in Panel A and the seventh column in Panel B. We report the positive and significant, and negative and significant proportions of the firm-level estimated coefficients for each of the 14 macroeconomic (technical) predictors in the third (eighth) and fourth (ninth) columns. The positive and significant (PS) and negative and significant proportion (NS) differences are reported in the fifth and tenth columns. t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.1.2. Firm-level PCA (1951.01 – 2011.12)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Market level		Firm-level				
P.C.	Slope coefficient	R^2(%)	PS(%)	NS(%)	PS(%) - NS(%)	R^2(%)	$ADJR^2$(%)
Panel A: Macroeconomic variables							
$\hat{F}_1^{MACRO}$	0.04 [0.48]	1.18	8.32	2.51	5.81 [3.94]***	2.22	0.77
$\hat{F}_2^{MACRO}$	0.07 [0.61]		21.87	2.56	19.31[13.59]***		
$\hat{F}_3^{MACRO}$	0.31 [2.48]***		12.83	3.91	8.92 [6.15]***		
$\hat{F}_{AVG}^{MACRO}$			14.34	2.99	11.35 [13.57]***		
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	0.12 [2.12]***	0.84	8.99	1.4	7.58 [5.13]***	0.57	0.08
Panel C: All predictors							
$\hat{F}_1^{ALL}$	0.11 [1.98]**	2.02	8.00	1.85	6.15 [4.16]***	2.74	0.81
$\hat{F}_2^{ALL}$	0.08 [0.93]		11.45	1.74	9.71 [6.63]***		
$\hat{F}_3^{ALL}$	0.31 [1.51]*		21.06	3.05	18.05 [12.66]***		
$\hat{F}_4^{ALL}$	0.04 [2.30]***		12.56	3.16	9.40 [6.45]***		
$\hat{F}_{AVG}^{ALL}$			13.27	2.45	10.82 [14.86]***		
					$R_{ALL}^2 - R_{MACRO}^2$	0.52 [38.50]***	0.03 [2.45]**
					$R_{ALL}^2 - R_{TECH}^2$	2.17 [97.23]***	0.73 [33.77]***

This table shows principal component analysis (PCA) results at market and firm-level respectively based on the following regression:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^P + \varepsilon_{t+1},$$

where y_{t+1} represents the market-level or individual firm level's log equity risk premium, respectively. $\hat{F}_{n,t}^P$ is the *n*th principal component extracted from the documented 14 macroeconomic variables ($P = MACRO$), 14 technical predictors ($P = TECH$), or all the 28 predictors together ($P = ALL$). We report collected market-level principal component prediction results from Neely et al.'s paper in the second and third columns. We report the positive and significant (PS), and negative and significant (NS) proportions of the firm-level estimated coefficients for each of these principal components in the fourth and fifth columns and the PS-NS proportion difference in the sixth column. We report the average R^2 and the average adjusted-R^2 in the last two columns. We calculate the difference in average R^2 and average adjusted R^2 between the PC-ALL model and PC-MACRO (PC-TECH) models in the last two rows of panel C. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.1.3. Size-sorted PCA (1951.01-2011.12)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
P.C.	S (Small)	2	3	4	L (Large)	S-L [t-stat]
			Panel A: Macroeconomic variables			
$\hat{F}_1^{MACRO}$	6.33	8.22	8.91	9.74	8.38	-2.05 [-2.20]**
$\hat{F}_2^{MACRO}$	20.24	21.79	20.76	24.14	22.45	-2.21 [-1.57]
$\hat{F}_3^{MACRO}$	9.89	12.13	13.05	12.27	16.82	-6.93 [-6.12]***
$\hat{F}_{AVG}^{MACRO}$	12.15	14.05	14.24	15.38	15.88	-3.73 [-2.06]**
R_{MACRO}^2	2.31	2.49	2.26	2.27	1.79	0.52 [7.17]***
			Panel B: Technical variables			
$\hat{F}_1^{TECH}$	12.02	11.50	7.82	6.74	6.89	5.13 [5.31]***
R_{TECH}^2	0.66	0.65	0.54	0.53	0.44	0.22 [7.74]***
			Panel C: All predictors			
$\hat{F}_1^{ALL}$	10.93	10.29	6.56	5.47	6.77	4.16 [4.53]***
$\hat{F}_2^{ALL}$	9.72	13.34	11.85	12.04	10.33	-0.61 [-0.57]
$\hat{F}_3^{ALL}$	20.18	20.64	19.84	21.89	22.73	-2.55 [-1.84]*
$\hat{F}_4^{ALL}$	8.97	9.66	12.48	13.31	14.52	-5.55 [-4.70]***
$\hat{F}_{AVG}^{ALL}$	12.71	18.21	17.40	17.53	18.37	-5.66 [-3.37]***
R_{ALL}^2	2.92	3.10	2.79	2.73	2.15	0.77 [9.85]***

This table shows the size-sorted estimate coefficients based on the principal component predictive regression results of equation (1) for the period between January 1951 to December 2011. All the positive and significant estimated coefficients are sorted into five groups based on the ranking of the firm's size, and we report the proportions for the firms with the smallest size in the second column and the largest size in the sixth column. The proportion difference between the smallest and largest firms is shown in the last column and the corresponding *t*-statistics in brackets comes from the estimated coefficient α_1 in the following linear regression:

$$D_{PS} = \alpha_0 + \alpha_1 * D_1 + \alpha_2 * D_2 + \alpha_3 * D_3 + \alpha_4 * D_4 + \varepsilon,$$

where D_{PS} is the dummy variable that equals one when the estimated coefficient of each firm is positive and significant at the 10%, 5%, or 1% level, otherwise zero. D_g (g=1, 2, 3, 4) is the dummy variable that equals one for firms in the four different size-sorted groups (exclude the largest size group with $g = 5$), otherwise zero. For example, $D_1 = 1$ means the firms are sorted in the smallest size group, otherwise zero. The *t*-statistics for the difference in average R^2 between the smallest and largest firms are in brackets and calculated from the equation above by replacing the D_{PS} with the R^2 from equation (1). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.1.4. PCA across business cycle (1967.06-2018.12) _ CFNAI

(1)	(2)	(3)	(4)	(5)	(6) [(2) - (3)]	(7) [(4) - (5)]	(8) [(2) - (4)]	(9)
	REC (β_n)		EXP (γ_n)		$PS^R - NS^R$	$PS^E - NS^E$	$PS^R - PS^E$	R^2(%)
Predictor	PS	NS	PS	NS	[t-stat]	[t-stat]	[t-stat]	
Panel A: Macroeconomic variables								
$\hat{F}_1^{MACRO}$	15.26	3.95	7.64	3.88	11.31 [8.20]***	3.75 [2.67]***	7.63 [5.59]***	
$\hat{F}_2^{MACRO}$	16.22	4.23	19.03	2.33	11.99 [8.72]***	16.69 [12.18]***	-2.81 [-2.12]**	4.71
$\hat{F}_3^{MACRO}$	11.32	10.97	8.99	2.77	0.35 [0.25]	6.23 [4.43]***	2.32 [1.69]*	
$\hat{F}_{AVG}^{MACRO}$	14.27	6.38	11.88	2.99	7.88 [9.94]***	8.89 [11.04]***	2.38 [3.05]***	
Panel B: Technical variables								
$\hat{F}_1^{TECH}$	7.93	6.07	7.14	4.56	1.86 [1.33]	2.58 [1.84]*	0.78 [0.56]	1.52
Panel C: All predictors								
$\hat{F}_1^{ALL}$	10.37	12.79	7.86	4.42	-2.42 [-1.77]*	3.44 [2.45]**	2.51 [1.81]*	
$\hat{F}_2^{ALL}$	16.11	8.69	6.60	5.12	7.41 [5.46]***	1.48 [1.05]	9.51 [6.66]***	
$\hat{F}_3^{ALL}$	14..62	8.28	10.67	3.65	6.34 [4.64]***	7.02 [5.02]***	3.95 [3.22]***	6.34
$\hat{F}_4^{ALL}$	14.84	9.67	11.82	3.91	5.17 [3.80]***	7.92 [5.68]***	3.02 [2.24]**	
$\hat{F}_{AVG}^{ALL}$	18.64	13.15	9.24	4.27	5.50 [7.16]***	4.97 [7.09]***	9.41 [12.99]***	
							$R_{ALL}^2 - R_{MACRO}^2$	1.63 [23.33]***
							$R_{ALL}^2 - R_{TECH}^2$	4.82 [74.89]***

This table reports firm-level predictability results across the business cycle using the following equation:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^P * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^P * DEXP_t + \varepsilon_{t+1},$$

where y_{t+1} represents the market-level or individual firm level's log equity risk premium, respectively. $\hat{F}_{n,t}^P$ is the *n*th principal component extracted from the documented 14 macroeconomic variables ($P = MACRO$), 14 technical predictors ($P = TECH$), or all the 28 predictors together ($P = ALL$). $DREC_t$ is the CFNAI recession dummy variable equal to unity when CFNAI-MA3 is less than -0.7 in month *t* and zero otherwise, and $DEXP_t = 1 - DREC_t$. We report the positive and significant (PS), and negative and significant (NS) proportions of the estimated coefficients for each of these principal components. The average R^2 is in the last column. The *t*-statistic for the proportion difference or the R^2 difference is in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.3.1. Definitions of firm characteristics

N	Variable	Name	Reference	Definitions of characteristics
1	age	Firm age	Jiang et al. (2005)	Number of years since the company's IPO year
2	baspread	Bid-ask spread	Amihud and Mendelson (1989)	Monthly averaged daily bid-ask spread divided by averaged daily spread
3	beta	Beta	Fama and MacBeth (1973)	Estimated market beta based on weekly returns and equal-weighted market returns for three years ending month $t - 1$ with at least 52 weeks of returns
4	betasqr	Beta squared	Fama and MacBeth (1973)	Market beta squared
5	bm	Book-to-market equity	Rosenberg et al. (1985)	Book value of equity divided by fiscal year-end market capitalization
6	bm_ia	Industry-adjusted book to market	Asness et al. (2000)	Industry adjusted book-to-market ratio
7	cfd	Cash-flow-to-debt	Ou and Penman (1989)	Earnings before depreciation and extraordinary items divided by the average of total liabilities
8	cp	Cash productivity	Chandrashekar and Rao (2009)	Fiscal year-end market capitalization plus long-term liabilities minus total assets scaled by cash and cash equivalents
9	CDI	Convertible debt indicator	Valta (2016)	A dummy variable equal to 1 for a company that has convertible debt obligations, zero otherwise
10	CR	Current ratio	Ou and Penman (1989)	Current assets divided by current liabilities
11	DTP	Depreciation / PP&E	Holthausen and Larcker (1992)	Depreciation divided by PP&E
12	dolvol	Dollar trading volume	Chordia et al. (2001)	Stock price times natural log of trading volume stock price from month $t - 2$
13	DTP	Dividend to price	Litzenberger and Ramaswamy (1982)	Annual total dividends divided by fiscal year-end market capitalization
14	ep	Earnings to price	Basu (1997)	Annual income before extraordinary items divided by fiscal year-end market cap

N	Variable	Name	Reference	Definitions of characteristics
15	ISC	Industry sales concentration	Hou and Robinson (2006)	2-digit SIC-fiscal-year sales concentration (sum of the squared percentages of sales in the industry for each company).
16	idiovol	Idiosyncratic return volatility	Ali et al. (2003)	Standard deviation of residuals of weekly returns on weekly equal-weighted market returns for three years before month-end
17	illq	Illiquidity	Amihud (2002)	Average of absolute daily return divided by daily dollar volume
18	indmom	Industry momentum	Moskowitz and Grinblatt (1999)	Equal-weighted average industry 12-month returns
19	IPO	New equity issue	Loughran and Ritter (1995)	An indicator equals one if the first year available on CRSP monthly stock file
20	lev	Leverage	Bhandari (1998)	Total liabilities divided by fiscal year-end market capitalization
21	maxret	Maximum daily return	Bali et al. (2011)	Maximum daily return during calendar month $t-1$
22	size	Size	Banz (1981)	Natural logarithm of market capitalization at the end of month $t-1$
23	mve_ia	Industry-adjusted size	Asness et al. (2000)	2-digit SIC industry-adjusted fiscal year-end market capitalization
24	PD	Price delay	Hou and Moskowitz (2005)	The proportion of variation in weekly returns for 36 months ending in month $t-1$ explained by four lags of weekly market returns incremental to contemporaneous market return
25	QR	Quick ratio	Ou and Penman (1989)	Value of current assets minus inventory divided by current liabilities
26	retvol	Return volatility	Ang et al. (2006)	The standard deviation of daily returns from month $t-1$
27	roic	Return on invested capital	Brown and Rowe (2007)	Annual earnings before interest and taxes minus non-operating income divided by non-cash enterprise value
28	STC	Sales to cash	Ou and Penman (1989)	Annual sales divided by cash and cash equivalents
29	STR	Sales to receivables	Ou and Penman (1989)	Annual sales divided by accounts receivable
30	SDI	Secured debt indicator	Valta (2016)	An indicator equal to 1 if the company has secured debt obligations

(*continued*)

N	Variable	Name	Reference	Definitions of characteristics
31	sin	Sin stocks	Hong and Kacperczyk (2009)	An indicator variable equal to 1 if a company's primary industry classification is in beer or alcohol, smoke or tobacco, or gaming
32	SP	Sales to price	Barbee et al. (1996)	Annual operating revenue divided by fiscal year-end market capitalization
33	std_dolvol	Volatility of liquidity	Chordia et al. (2001)	The monthly standard deviation of daily dollar trading volume
34	std_turn	Volatility of liquidity	Chordia et al. (2001)	The monthly standard deviation of daily share turnover
35	tang	Debt capacity/firm tangibility	Almeida and Campello (2007)	Cash holdings + 0.715 × receivables + 0.547 × inventory + 0.535 × PPE/total assets
36	turn	Share turnover	Datar et al. (1998)	Average monthly trading volume for the most recent three months scaled by the number of shares outstanding in the current month
37	zero trade	Zero trading days	Liu (2006)	Turnover weighted number of zero trading days for most recent one month

(*continued*)

This table presents detailed definitions of the 37 firm characteristics applied in this study to estimate the enduring momentum probabilities.

Table A.3.2. Partial likelihood estimates of enduring momentum portfolio returns

		Panel A: Winners		Panel B: Losers	
N	Variable	beta	P-value	beta	P-value
1	age	0.0015	<.0001	0.0053	<.0001
2	baspread	-1.5241	<.0001	0.5224	<.0001
3	beta	-0.0780	<.0001	0.0133	0.2539
4	betasq	0.0150	<.0001	-0.0059	0.0953
5	bm	0.0130	0.0008	0.0591	<.0001
6	bm_ia	0.0000	<.0001	0.0000	0.0605
7	cashdebt	-0.0054	0.0042	0.0082	0.0002
8	cashpr	0.0001	0.1067	0.0000	0.8077
9	convind	0.0391	<.0001	-0.0653	<.0001
10	currat	-0.0003	0.8752	-0.0014	0.4605
11	depr	-0.0327	<.0001	0.0021	0.7323
12	dolvol	0.0091	0.0061	-0.0521	<.0001
13	dy	0.9350	<.0001	-0.1528	0.0850
14	ep	0.0327	<.0001	-0.0140	0.1255
15	herf	0.0812	0.0048	-0.2412	<.0001
16	idiovol	0.3630	<.0001	0.3761	0.0002
17	ill	-0.0001	0.7687	0.0005	<.0001
18	indmom	0.0183	0.0204	0.0091	0.3455
19	IPO	0.0001	0.9927	-0.1124	<.0001
20	lev	0.0011	0.1193	-0.0109	<.0001
21	maxret	-1.5574	<.0001	1.4422	<.0001
22	mve	0.0220	<.0001	0.0428	<.0001
23	mve_ia	0.0000	<.0001	0.0000	<.0001
24	pricedelay	-0.0001	0.9492	-0.0060	0.0270
25	quick	0.0022	0.2849	0.0034	0.1177
26	Diff_retvol	2.8002	<.0001	-4.1187	<.0001
27	roic	0.0036	0.1434	0.0105	<.0001
28	salecash	0.0001	<.0001	0.0000	0.4624
29	salerec	-0.0003	0.0054	-0.0001	<.0001
30	securedind	-0.0588	<.0001	-0.0319	<.0001
31	sin	-0.0679	0.0051	0.0605	0.0748
32	SP	-0.0127	<.0001	0.0076	<.0001
33	std_dolvol	-0.0038	0.6997	0.0272	0.0174
34	std_turn	-0.0012	0.0024	-0.0024	<.0001
35	tang	-0.2163	<.0001	0.0305	0.1363
36	turn	-0.0006	0.7982	-0.0170	<.0001
37	zerotrade	0.0196	<.0001	0.0028	0.0696
	R^2	2.77%		3.38%	

This table shows the partial likelihood estimation results for the multiple-variable Cox PH model of the enduring momentum strategy. Panel A (B) indicates the estimated coefficients for all 37 firm characteristics for winner (loser) firms, and we report the R^2 in the last row.

Table A.3.3. Summary statistics of estimated enduring momentum probability

N	Mean	std	Median	Max	Min
Panel A: Winners					
1	0.580	0.070	0.581	0.782	0.313
2	0.425	0.079	0.423	0.679	0.166
3	0.300	0.079	0.295	0.579	0.082
4	0.200	0.071	0.192	0.481	0.037
5	0.120	0.058	0.110	0.381	0.013
6	0.047	0.036	0.038	0.250	0.002
Panel B: Losers					
1	0.581	0.090	0.588	0.793	0.237
2	0.425	0.099	0.427	0.690	0.116
3	0.296	0.096	0.292	0.587	0.053
4	0.194	0.083	0.185	0.482	0.022
5	0.112	0.064	0.100	0.373	0.008
6	0.045	0.039	0.034	0.240	0.001

This table reports the summary statistics of the enduring momentum probability from the Cox PH model for winner and loser firms to perform as winners and losers during the six-month holding period.