Forecasting Individual Stock Returns Using Macroeconomic and Technical Variables

Hui Zeng*
Massey University
h.zeng@massey.ac.nz

Ben R. Marshall
Massey University
b.marshall@massey.ac.nz

Nhut H. Nguyen
Auckland University of Technology
nhut.nguyen@aut.ac.nz

Nuttawat Visaltanachoti
Massey University
n.visaltanachoti@massey.ac.nz

Abstract

We show that the previously documented predictability of macroeconomic and technical variables for market returns is also evident in individual stocks. Technical variables generate better predictability on firms with larger limits to arbitrage (smaller, illiquid, volatile firms), while macroeconomic variables better predict firms with lesser limits to arbitrage. Macro indicators perform well across the business cycle but comparatively stronger in recessions, while technical variables exhibit strong predictive power in recessions but somewhat weaker in expansions. Moreover, macroeconomic variables have better prediction performance on low arbitrage constraint firms in recession while technical indicators capture more forecast information for high arbitrage constraint firms in expansion.

JEL Classification Codes: C58, E32, G11, G12, G17
Keywords: Firm level predictability, macroeconomic and technical predictors, principal component analysis (PCA), limits to arbitrage, cross-sectional predictability, business cycle.

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Corresponding author: Hui Zeng, School of Economics and Finance, Massey University, Private Bag 102904, North Shore Auckland, New Zealand. Ph: 649 414 0800, Fax: 43 180, E-mail: h.zeng@massey.ac.nz

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Abstract

We show that the previously documented predictability of macroeconomic and technical variables for market returns is also evident in individual stocks. Technical variables generate better predictability on firms with larger limits to arbitrage (smaller, illiquid, volatile firms), while macroeconomic variables better predict firms with lesser limits to arbitrage. Macro indicators perform well across the business cycle but comparatively stronger in recessions, while technical variables exhibit strong predictive power in recessions but somewhat weaker in expansions. Moreover, macroeconomic variables have better prediction performance on low arbitrage constraint firms in recession while technical indicators capture more forecast information for high arbitrage constraint firms in expansion.

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1. Introduction

Both macroeconomic variables and technical indicators can be used to forecast market-level equity returns (e.g., Goyal and Welch, 2008; Brock, Lakonishok, and LeBaron, 1992). Moreover, Neely, Rapach, Tu, and Zhou (2014) show that these variables can complement each other in forecasts of the market risk premium. We contribute to the literature by considering the predictive ability of macroeconomic and technical factors for individual stock returns[1].

We consider whether there is variation of predictability in the cross-section based on the extent of limits to arbitrages in different stocks and whether the predictability changes through time. Campbell, Lettau, Malkiel, and Xu (2001) find that investors bear higher idiosyncratic risks by investing in individual stocks rather than the aggregate market and 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.

Our study for individual stock returns predictability builds on the framework in Neely, Rapach, Tu, and Zhou (2014, NRTZ hereafter). We follow NRTZ and extract three principal components from the fourteen macroeconomic variables (PC-MACRO), one principal component from the fourteen technical indicators and four principal components from all the twenty-eight predictors. We contribute to the literature in three ways. First, we investigate the forecasting roles of macroeconomic and technical predictors at the firm level. We find that

[1] While the majority of papers consider predictability using market returns, a number of 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.

market-level predictability evident in NRTZ shows up at the firm level. Both fundamental indicators and technical variables predict individual stock returns.

Second, we consider the impact of proxies for limits to arbitrage, including firm size, liquidity and volatility on predictability. We find that macroeconomic variables perform better in predicting large size, high liquidity, and low volatility with low arbitrage constraint stocks, technical indicators exhibit stronger predictive power for the high limits of arbitrage firms (smaller, illiquid, volatile firms). A sizable literature shows that large, 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]. On the contrary, technical analysis is widely applied for assessing stocks with less efficiency and the prediction mainly based on past prices and perhaps other past statistics decisions[3].

Third, we assess the variation of individual stock predictability over the business cycle and test whether the influence of limit of arbitrage changes through time. Our results show that macroeconomic variables display good predictive ability across the business cycle but even better in recessions while technical indicators show stronger predictive power during tight periods but are somewhat weaker in expansions. Furthermore, macroeconomic variables can better predict low arbitrage constraint firms; that is, the large, high liquidity firms in recessions. However, technical indicators consistently show more significant evidence of stronger

[2] Papers that test the relationship between macroeconomic indicators and firm size include Chan, Chen, and Hsien (1985), who find that macroeconomic variables can well explain size effect, and Chan and Chen (1991) who indicate that large firms are more effective in dealing with market economic information than smaller firms are. Chen and Mahajan (2010) find a positive relationship between macroeconomic factors and corporate liquidity.

[3] Delong et al. (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.

predictive power for high limits of arbitrage firms (smaller, low liquidity and volatile firms) in expansions.

Our paper contributes to several strands of the literature. First, we add to predictability papers. Goyal and Welch (2008) claim that macroeconomic variables cannot predict the aggregate stock market. Similarly, Rapach, Wohar, and Rangvid (2005) state that few macroeconomic variables have predictive power based on worldwide aggregate stock markets. Other recent studies which employ fundamental variables include Maio and Philip (2015) and Rapach, Ringgenberg, and Zhou (2016). In investigating the predictive roles of technical indicators, earlier empirical studies like Lo, Mamaysky, and Wang (2000) find significant prediction evidence by applying technical analysis while most recent research of Lin (2018) demonstrates that his new technical analysis index can improve the predictive power in forecasting the aggregate market. NRTZ evaluate both fundamental and technical variables in predicting equity returns. However, these studies do not comprehensively analyze how macroeconomic variables and technical indicators predict individual stock returns. Consequently, we fill the gap of predictability in the individual section by applying both the two sets of indicators and find highly consistent prediction evidence of previous market level findings.

Second, we add to literature around limits to arbitrage. Shleifer and Vishny (1997) suggest that limited and costly arbitrage opportunities drive stock prices far away from their fundamental value. This inefficient arbitrage of stock returns creates predictability opportunities. Many papers illustrate that high-constrained firms earn higher risk premium returns (e.g., Whited and Wu, 2006; Li and Zhang, 2010). Therefore, we motivate to investigate whether there is variation in individual stock predictability based on the extent of limits to arbitrages, mainly on the three main proxies: firm size, stock return volatility and illiquidity. To our knowledge, we are the first paper to document a predictive link between arbitrage proxies-sorted individual firms with both macroeconomic variables and technical indicators. Our results are consistent with related areas of theoretical and empirical studies. Li and Zhang (2010) indicate larger limits of arbitrage firms earn higher expected returns by employing q-theory. Lam and Wei (2011) find that there is a significant positive relationship between limits to arbitrage and the asset growth anomaly.

Third, we contribute to the literature that considers variation in predictability over time. Fama and French (1989) find that the default spread and the dividend yield display different roles in tracking expected returns across the business cycle. Pesaran and Timmermann (1995) indicate that the predictive power of various economic factors are in volatile periods.

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

2. Data and Method

2.1. Data

The sample in our paper is all common stocks trade on the NYSE, AMEX, and NASDAQ exchanges with available monthly stock return data retrieved from the Centre for Research in Security Press (CRSP) database. In order to have comparisons with prior market predictability, we follow the sample data spanning of NRTZ that starts from January 1951 and ends in December 2011. In order to keep sufficient observation of regression, we keep firms that have over ten years' monthly returns. After excluding delisting stocks and deleting the observations with a monthly return less than 100%, 8,695 firms remain at the end. There are two sets of parallel control variables in our paper: the first is the 14 macroeconomic variables by following the variable definitions detailed in Goyal and Welch's[4] (2008) paper while the other one is the 14 technical indicators applied from NRTZ's[5] study.

2.2. Method

2.2.1. Principal Components Predictive Regression

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

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

where y_{t+1} is one of the 8,695 equity returns in excess of risk-free rate in month $t+1$; $\hat{F}_{n,t}^{P}$ represents the *n*-th principal components which incorporate information from the document 14 fundamental variables (P=MACRO), 14 technical predictors (P=TECH), or all the 28 predictors together (P=ALL). Comparing with market level predictive results, we generally follow NRTZ in selecting the components value N. The value of N equals three for 14 macroeconomic variables; N equals one for the 14 technical variables; and N equals four, given all the 28 predictors taken together. The critical value applied in our in-sample regression based on the heteroscedasticity-consistent t-statistics by applying the Newey West test under the hypothesis of $H_0: \beta_i = 0$ against $H_A: \beta_i \neq 0$.

The predictability results are categorized based on the ranking of three arbitrage proxies: illiquidity, volatility, and size. First, we measure the monthly volatility of each stock by the

[4] Much appreciation for Amit Goyal making these data available on his website
[5] Much appreciation for Dave Rapach making these data available on his website

standard deviation of its daily return. Second, we directly apply the monthly capitalisation to rank each stock into different size groups. Last, the illiquidity index $ILLIQ$ is calculated by Amihud's (2002) measure defined as follows:

$$ILLIQ_t = 10^6 \frac{1}{D_t} \sum_d \frac{|R_t|}{DVOL_t} \tag{2}$$

where R_t is the daily return in month *t*; $DVOL_t$ is the dollar volume which equals daily price times daily 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. Each firm's monthly illiquidity index is calculated from the average of daily illiquidity value.

Following the cross-sectional prediction investigation above, we further engage the predictability change over time by applying the following principal component predictive regression:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^N * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^N * DEXP_t + \varepsilon_{t+1} \tag{3}$$

where the added $DREC_t$ ($DEXP_t$) represents the recession (expansion) dummy variable that equals unity when month t in recession (expansion) and zero otherwise, $DEXP_t = 1 - DREC_t$. We apply four alternative specifications in defining the recession dummy variable $DREC_t$ and the expansion dummy variable $DEXP_t$. The first is the National Bureau of Economic Research (NBER)[6] dated business cycle expansions and recessions, $DREC_t$ equals to unity if the economy is in recession and zero otherwise, $DEXP_t = 1 - DREC_t$. The second alternative is defined by applying data from Chicago Fed National Activity Index (CFNAI)[7],

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

the recession (expansion) dummy indicator equals to unity when CFNAI-MA3 is less (greater) than -0.7 in month *t* and zero otherwise. We estimate the third alternative by following Cooper, Gutierrez, and Hameed (2004) who measure economic condition based on past three years' financial market performance. If the cumulative return on a broad stock market index of the past 36 months is greater (less) than zero, the expansion (recession) dumm Amihud y indicator is defined as unity and zero otherwise. The last alternative measure comes from Hameed, Kang, and Viswanathan (2010) who directly use the market-value-weighted stock index to estimate the economic conditions, and the recession (expansion) dummy variable equal to unity if and only if the market return is less (greater) than zero.

2.2.2. Simple Linear Regression

Principal component analysis parsimoniously incorporates information from a large number of predictors. In comparison, we apply the conventional simple linear regression model as our robustness test as follows:

$$y_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

where y_{t+1} is the excess return of each individual stock at month *t+1*; $x_{i,t}$ is one of the 14 macroeconomic or 14 technical predictors in month t. We calculate the Newey West t-statistics of each predictive regression that are consistent with the above principal component analysis. The estimated results of each firm are sorted into five groups based on three arbitrage proxies, illiquidity, volatility, and size, which are the same in the principal component predictive analysis.

Exploring the time effect on the predictability of individual stocks, we apply the recession dummy variable to interact with each predictor in the regression to detect the predictability of individual stocks across the business cycle:

$$y_{t+1} = \alpha_i + \beta_{1,i} x_{i,t} * DREC_t + \beta_{2,i} x_{i,t} * DEXP_t + \varepsilon_{i,t+1} \tag{5}$$

where $x_{i,t} * DREC_t$ ($x_{i,t} * DEXP_t$) is the interaction between the recession (expansion) dummy variable and one of the macroeconomic or technical predictors in month t. We report the main results by applying the NBER business cycle.

3. Empirical Results

3.1. Firm Level Predictability Evidence

Table 1 contains the principal components predictive regression results collected from NRTZ's paper and our firm level study which is summarised by proportion. Market level results in the second column shows that macroeconomic variables can positively predict an aggregate market based on the principal components while the R^2-statistics in the third column provide the complementary predictive evidence of macroeconomic and technical predictors in forecasting aggregate markets. The sum of the R^2-statistics for the PC-MACRO (1.18%) and PC-TECH (0.84%) models in panels A and B are equal to the R^2-statistics for PC-ALL (2.02%) model in panel C.

In comparison, the firm-level principal components predictive regression results report in the other columns of table 1. All the estimate coefficients significant at 10% level are sorted into positive and negative proportions in the fourth and fifth columns. We can observe that all the positive and significant (PS) proportions are typically higher by six to twenty percent than when there is a negative and significant (NS) proportion. The row immediately close to the last component of panel B and panel C reports the average positive (negative) significant proportion that is calculated by summing the numbers of positive (negative) and significant slope coefficients and then dividing by the total number of firms times the value *N*. The aggregate results include consistent higher positive and significant proportions of estimated coefficients. At first glance, the average R^2 statistic is comparatively larger for the PC-MACRO model in panel A than the PC-TECH model in panel B. Additionally, the sum value of average R^2 and adjusted-R^2 for firm level PC-MACRO (2.22%, 0.77%) and PC-TECH (0.57%, 0.08%) is closely equal to the average R^2 and adjusted-R^2 for PC-ALL (2.74%, 0.81%) model in panel C. Moreover, we contract significant tests for the difference of R^2 statistic between the average R^2 (adjusted-R^2) for PC-ALL models and the PC-MACRO or PC-TECH models in the last two rows of panel C to confirm the suggestion of NRTZ at firm level that macroeconomic variables and technical indicators essentially contain complementary prediction information.

[Please Insert Table 1 About Here]

The conventional regression results are reported in appendix 1 which are robust to the principal component predictive approach in table 1. All the macroeconomic variables and 13 of 14 technical variables exhibit stronger predictive power in positively forecasting individual firms returns that are highly consistent with the principal component predictive regression results in table 1.

3.2. Cross sectional Predictability

The limits-to-arbitrage hypothesis suggests that higher limits of arbitrage firms receive higher risk returns than low limits of arbitrage firms. 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).

Tale 2 shows the size-sorted predictive regression results at the firm level. The estimation results for the PC-MACRO model in panel A indicate that macroeconomic variables have higher predictive ability for larger firms, whereas the estimate proportion results of the PC-TECH model in panel B exhibit stronger forecasting power for smaller firms. The results of the PC-All model in panel C imply that macroeconomic variables and technical variables actually complement each other in cross section predictability of individual stocks. Four principal components in the PC-ALL model essentially reflect the predictive message of the PC-MACRO model in panel A and the PC-TECH in panel B. The significant proportion of first principal component ($\hat{F}_1^{ALL}$) in the PC-ALL model has a higher magnitude for smaller firms which is highly consistent with the findings on panel B ($\hat{F}_1^{TECH}$), whereas the other three components show stronger predictive power for large size firms that reveal similar information on panel A of the three macroeconomic components ($\hat{F}_1^{ECON},\ \hat{F}_2^{ECON},\ \hat{F}_3^{ECON}$).

These findings confirm NRTZ's (2014)[8] suggestion and are further evidence that macro variables and technical indicators provide complementary information in the cross section prediction based on the extent of limits of arbitrage.

[8] Neely et al. (2014) illustrate that the first principal component in the PC-ALL model closely responds to the technical indicators while the other three principal components of PC-ALL load heavily on PC-MACRO (1), PC-MACRO (2), and PC-MACRO (3), respectively.

[Please Insert Table 2 About Here]

Average R^2- statistics of all the three panels in table 2 are higher for smaller firms and diminish when the firm size increases. In addition, the sum of the average R^2 statistics for the PC-MACRO (with components extracted from 14 macroeconomic variables) model and the PC-TECH model (with components extracted from 14 technical variables) equals the average R^2 statistic for the PC-ALL (with components extracted from the entire variables) model. These findings indicate that macro and technical predictors complement each other in predicting size-sorted firms. Moreover, Appendix 2 delivers the same information as table 2 by applying univariate simple linear regression. The majority of macroeconomic variables exhibit higher predictive ability for large stocks, whereas technical indicators do better in forecasting small firms[9].

[Please Insert Table 3 About Here]

The liquidity-sorted principal component predictive regression results in table 3 have a similar predictive pattern to the size-sorted findings in table 2. Panel A of Table 3 shows that macroeconomic variables have stronger predictive power for higher liquidity firms especially for the first and third component, $\hat{F}_1^{ECON}$, and $\hat{F}_3^{ECON}$. The larger firms show significantly higher proportions in predicting individual stocks for the first and third principal components in panel A. However, technical predictors in panel B display contrary roles in that they show significantly stronger forecasting power for low liquidity firms. Panel C reports the prediction results by the four principal components extracted from the entire 28 variables.

[9] For brevity, the complete results of liquidity and volatility sorted predictability results are reported in the internet appendix.

We can learn that macroeconomic variables and technical indicators generate complementary predictive information in forecasting individual stock returns. The first principal component ($\hat{F}_1^{ALL}$) reports identical predictive information of the technical component in panel B, while the other three components ($\hat{F}_1^{ALL}$, $\hat{F}_2^{ALL}$, $\hat{F}_3^{ALL}$) in panel C again have the most instances of generating similar predictive messages to the three macroeconomic components in panel A. The R^2 statistic in the last row of each panel diminishes with increase of liquidity. Moreover, the sum of the R^2- statistic in panel A and B equals the R^2- statistic in panel C which provides the consistent information of size-sorted results in table 2 that further support the complementary prediction evidence of macroeconomic variables and technical indicators in predicting liquidity-sorted individual stocks.

[Please Insert Table 4 About Here]

The volatility-classified results in table 4 report that three out of four principal components extracted from macroeconomic variables in panel A can better predict low volatility firms while technical indicators in panel B primarily capture the fluctuations of volatile firms. The four principal components extracted from the entire variables complementary load the predictive information from macro variables and technical indicators. The evidence from the first principal component is weaker than presented in the size-sorted and liquidity-sorted finings, whereas the other three components were generally consistent with the prediction results of macro principal components in panel A. We can see that the magnitude of the R^2- statistic is significantly reduced by the increase of volatility at the end of each panel, and the sum of the R^2- statistic in panels A and B for the PC-MACRO and the PC-TECH roughly equals the R^2- statistic in panel C for PC-ALL models. Thus, the results for R^2-statistic keep supporting our hypothesis of volatility-sorted firms that low volatility firms (low limits of arbitrage firms) can be better predicted by macroeconomic factors while technical indicators do better in forecasting volatile firms (high limits of arbitrage firms).

Taken together, the results based on table 2 to table 4 suggest several takeaways for the limits to arbitrage effecting work on the cross-sectional predictability of individual stock returns. First, macroeconomic variables and technical indicators capture complementary information in the cross-sectional predictability of individual returns based on the extent of the limits of arbitrage. Principal components derived from macroeconomic variables play higher predictive ability in forecasting large, liquid and low volatility firms, while principal components extracted from technical indicators show stronger forecast power to high limits of arbitraged (smaller, low liquidity, and volatile firms) firms.

3.3. Predictability during Recessions and Expansions

The main results in Section 3.2. explain the influence of different aspects of the limits of arbitrage on the predictability of individual stock returns by using both macroeconomic variables and technical indicators. In this section, we further investigate the variation of firm level predictability across the economic cycle.

[Please Insert Table 5 About Here]

The results shown in table 5 report the overall predictability of individual stock returns across the business cycle. Panel A of table 5 indicates that principal components extracted from macroeconomic variables perform well through time but comparatively better in recessions. Technical indicators in panel B demonstrate that technical indicators have good forecast performance in recessions but are somewhat weaker in expansions and comparatively show significantly higher predictive proportions during recessions. The average R^2- statistic for the PC-ALL model in panel C is 5.18%, which generally equals the sum of the R^2- statistic for the PC-MACRO model (4.17%) and the PC-TECH model (1.11%). In addition, we report the significant test of the two pairs of the R^2- the statistical difference between the PC-ALL model with the PC-MACRO model, and the PC-ALL model with the PC-TECH model at the bottom of panel C. The significant t-statistics for both of the two pairs of R^2- statistic difference suggest that the macro variables and technical indicators capture different predictive information over the business cycle.

Appendix 3 contains predictive information by applying the alternative recession dummy variable calculated by using the CHANI-MA3 index which is highly consistent with the findings in table 5.

3.4. Cross-Sectional Predictability during Recessions and Expansions

In this section, we consider the influence of economic conditions on the cross-section predictability of individual stock returns based on the extent of limits to arbitrage.

[Please Insert Table 6 About Here]

Table 6 represents the size-sorted principal component predictive regression results across the business cycle. For comparison, we only report the results for the largest firms and smallest firms. The fourth column in panel A shows that macroeconomic variables generally do better in predicting large firms in recessions especially for the third principal components and the average level as well. However, the proportional estimate results in panel B reveal the opposite prediction roles of technical indicators that the extracted principal components show stronger predictive power for smaller firms on expansions but weaker during recessions.

Turning to the results in panel C, we can see that the first principal component extracted from the entire variables exhibits similar predictive information of technical predictors in panel B that provide more predictive information for small firms in expansions. The other three components in panel C exhibit closer identical information of macroeconomic variables in panel A that better forecast large firms in expansions. Moreover, the comparison results in the last column show that the difference between smaller and larger firms' predictability are higher in expansions which indicates that the size effect for all the principal components is higher during expansions. Smaller firms have significantly higher R^2-statistics in the prediction regression than large firms in all the three panels.

Table 7 shows the principal component analysis results sorted by Amihud's (2002) illiquidity measure. We compare the estimate results for the highest illiquidity firms and the lowest illiquidity firms during recessions and expansions, respectively.

[Please Insert Table 7 About Here]

The principal components extracted from macroeconomic variables in panel A exhibit higher predictive ability for high liquidity firms in both recessions and expansions. However, turning to the results of the technical indicators in panel B, we can see that the technical indicators do better in measuring the movement of low liquidity firms in expansions. In addition, panel C provides complementary predictive information for macroeconomic and technical indicators for liquidity-sorted firms. The first principal component mimics the predictive ability of technical indicators in panel B while the other three exhibit similar information of macroeconomic variables in panel A. Additionally, the difference in liquidity-sorted proportion difference between recessions and expansions is significantly negative in panel B and panel C which indicate that the liquidity effect is more obvious in expansions for technical variables. Moreover, the R^2-statistics are higher for the low liquidity firms of all three principal components' predictive regressions.

Table 8 presents the results of volatility-sorted individual firms during recessions and expansions, respectively.

[Please Insert Table 8 About Here]

As shown in Table 8, the predictive ability of macroeconomic variables and technical indicators are quite different for the volatility-sorted firms during recessions and expansions. The empirical results in panel A of table 8 indicate that macroeconomics generally have higher predictive ability for high volatility firms in recessions and low volatility firms during expansions. However, turning to the results of technical indicators in panel B of Table 8, we can see those technical indicators show different predictive performance from macroeconomic indicators that better predict the low volatility firms during recessions but have stronger power in forecasting high volatility firms in expansions. The comparison results in the last column report that the macroeconomic variables better predict high volatility firms in recessions and the proportion difference is higher in recessions, whereas principal components in panel B and C have the opposite conclusion. The R^2- statistic in the last row of each panel give the complementary predictive evidence of macroeconomic and technical indicators, the R^2-statistic for the PC-ALL model general equals the sum of the R^2- statistic for the PC-MACRO and PC-TECH models.

4. Conclusions

We investigated firm-level predictability by both macroeconomic variables and technical indicators from previous documents. While these two sets of predictors are thoroughly investigated in the aggregate section of financial market predictability, much less is known at individual-level forecasting. Therefore, we apply previous document macroeconomic variables and technical indicators in comprehensively exploring firm level predictability.

First, we find that market level predictability can also be evident at the firm level, and both macroeconomic variables and technical indicators can significantly predict individual stock returns that count with larger positive proportions. Second, our results suggest that macroeconomic variables and technical variables complement each other in predicting individual firms based on the extent of their limits to arbitrage. Macroeconomic variables show stronger predictive power in forecasting firms with lower arbitrage constraints (large, liquid, low volatility firms) while technical variables catch more predictive information for small, low liquidity and high volatility firms. Third, we examine firm-level predictability over economic states and find that macroeconomic variables have good prediction performance across the business cycle but even better in recessions while technical indicators mainly exhibit predictive ability during recessions. Fourth, the cross-sectional predictive results over time indicate that technical indicators consistently show stronger predictive power for high limits of arbitrage firms (smaller, low liquidity and volatile firms) in expansions. However, macroeconomic variables can better predict the large size, high liquidity firms (with low limits of arbitrage) in recessions, but low volatility firms in expansions.

References

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), pp.31-56.

Boudoukh, J., Michaely, R., Richardson, M., & Roberts, M. R. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *Journal of Finance*, *62*(2), 877-915.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, *47*(5), 1731-1764.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, *56*(1), 1-43.

Chan, K. C., & Chen, N. F. (1991). Structural and return characteristics of small and large firms. *Journal of Finance*, *46*(4), 1467-1484.

Chan, K. C., Chen, N. F., & Hsieh, D. A. (1985). An exploratory investigation of the firm size effect. *Journal of Financial Economics*, *14*(3), 451-471.

Chen, N., & Mahajan, A. (2010). Effects of macroeconomic conditions on corporate liquidity—international evidence. *International Research Journal of Finance and Economics*, *35*(35), 112-129.

Cooper, M. J., Gutierrez Jr, R. C., & Hameed, A. (2004). Market states and momentum. *Journal of Finance*, *59*(3), 1345-1365.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703-738.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), 23-49.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance*, *65*(1), 257-293.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance*, *56*(2), 699-720.

Lam, F. E. C., & Wei, K. J. (2011). Limits-to-arbitrage, investment frictions, and the asset growth anomaly. *Journal of Financial Economics*, *102*(1), 127-149.

Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, *55*(5), 2017-2069.

Li, D., & Zhang, L. (2010). Does q-theory with investment frictions explain anomalies in the cross section of returns?. *Journal of Financial Economics*, *98*(2), 297-314.

Lin, Q. (2018). Technical analysis and stock return predictability: An aligned approach. *Journal of Financial Markets*, *38*, 103-123.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *55*(4), 1705-1765.

Maio, P., & Philip, D. (2015). Macro variables and the components of stock returns. *Journal of Empirical Finance*, *33*, 287-308.

Mookerjee, R., & Yu, Q. (1997). Macroeconomic variables and stock prices in a small open economy: The case of Singapore. *Pacific-Basin Finance Journal*, *5*(3), 377-388.

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, *60*(7), 1772-1791.

Pesaran, M. H., & Timmermann, A. (1995). Predictability of stock returns: Robustness and economic significance. *Journal of Finance*, *50*(4), 1201-1228.

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563-602.

Rapach, D. E., Ringgenberg, M. C., & Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, *121*(1), 46-65.

Rapach, D. E., Wohar, M. E., & Rangvid, J. (2005). Macro variables and international stock return predictability. *International Journal of Forecasting*, *21*(1), 137-166.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*(1), 35-55.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, *70*(5), 1903-1948.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*(4), 1455-1508.

Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, *19*(2), 531-559.

Table 1: Firm Level Principal Component Predictive Regression

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Market level		Firm level				
Predictor	Slope coefficient	R^2(%)	PS(%)	NS(%)	PS(%) - NS(%)	R^2(%)	$ADJR^2$(%)
Panel A: Macroeconomic variables							
$\hat{F}_1^{ECON}$	0.04 [0.48]	1.18	8.32	2.51	5.81 [3.94]***	2.22	0.77
$\hat{F}_2^{ECON}$	0.07 [0.61]		21.87	2.56	19.31 [13.59]***		
$\hat{F}_3^{ECON}$	0.31 [2.48]***		12.83	3.91	8.92 [6.15]***		
$\hat{F}_{AVG}^{ECON}$			14.34	2.99	11.35 [13.57]***		
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	0.12 [2.12]***	0.84	8.99	1.41	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]***		
					$R^2(\hat{F}^{ALL}) - R^2(\hat{F}^{ECON})$	0.52 [38.50]***	0.03 [2.45]**
					$R^2(\hat{F}^{ALL}) - R^2(\hat{F}^{TECH})$	2.17 [97.23]***	0.73 [33.77]***

Table 1 shows principal component analysis (PCA) results at market and firm-level respectively based on the following regression:

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

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 fundamental 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. The positive and negative significant proportions of estimate coefficients of firm-level principal component predictive regression report in the fourth and fifth columns and their difference report in the sixth column. All the regression results show significantly higher positive proportion for all the three principal component predictive models. We report the average R^2 statistics and average adjusted-R^2 average of firm-level regression in the last two columns of table 1. We calculate the difference in average R^2 and average adjusted R^2 between PCA-ALL model and PC-MACRO (PC-TECH) model in the last two rows of panel C.

Table 2: Size-Sorted Principal Component Predictive Regression Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Positive and Significant Proportion			
Component	S (Small)	2	3	4	L (Large)	S-L [t-stat]
			Panel A: Macroeconomic variables			
$\hat{F}_1^{ECON}$	6.33	8.22	8.91	9.74	8.38	-2.05 [-2.20]**
$\hat{F}_2^{ECON}$	20.24	21.79	20.76	24.14	22.45	-2.21 [-1.57]
$\hat{F}_3^{ECON}$	9.89	12.13	13.05	12.27	16.82	-6.93 [-6.12]***
$\hat{F}_{AVG}^{ECON}$	12.15	14.05	14.24	15.38	15.88	-3.73 [-2.06]**
R_{ECON}^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]***

Table 2 shows the size-sorted estimate coefficients based on the principal component predictive regression results of equation (1). All positive and significant estimate coefficients are sorted into five groups by the firm's size ranking. The proportions for the smallest firms (S) to the largest firms (L) in the second to sixth columns show that macroeconomic variables in panel A have stronger predictive power for large firms while technical indicators in panel B display higher predictive ability for smaller size firms. Moreover, the first principal component of PC-ALL model in panel C show similar predictive information of technical variables in panel B while the rest three principal components display close identical prediction information of macroeconomic variables in panel A. The average R^2- statistic of all the firms for each model report in the last row of each panel, which is larger in magnitude for smaller firms. The proportions difference between smallest and largest firm shows in the last column of table 2 and the corresponding t-value inside the bracket come from the estimate 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 positive and significant dummy variable, if the estimated coefficient of each firm is positive and significant at the 10% level then D_{PS} equal to the unit, otherwise zero. D_i is the dummy variable of individual firm's size group. For example, if a firm in the smallest size group, D_1 equals to the unit, otherwise zero. The t-statistic of the difference average R^2-statistic between the smallest and largest firms is also calculated by the equation above with replacement of the D_{PS} to the R^2- statistic from the regression of equation (1).

Table 3: Liquidity-Sorted Principal Component Predictive Regression Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Positive and Significant Proportion						
Component	L (Low Liquidity)	2	3	4	H (High Liquidity)	L-H [t-stat]
Panel A: Macroeconomic variables						
$\hat{F}_1^{ECON}$	6.04	8.28	8.86	9.32	9.09	-3.05 [-3.26]**
$\hat{F}_2^{ECON}$	21.22	21.33	21.79	23.98	21.05	0.17 [0.12]
$\hat{F}_3^{ECON}$	9.20	10.70	12.71	16.39	15.18	-5.98 [-5.29]**
$\hat{F}_{AVG}^{ECON}$	12.15	13.44	14.45	16.56	15.11	-2.95 [-1.62]
R_{ECON}^2	2.35	2.34	2.14	2.32	1.96	0.39 [5.35]***
Panel B: Technical variables						
$\hat{F}_1^{TECH}$	11.62	10.93	8.63	7.36	6.44	5.18 [5.35]***
R_{TECH}^2	0.65	0.60	0.56	0.52	0.50	0.15 [5.18]***
Panel C: All predictors						
$\hat{F}_1^{ALL}$	11.04	8.68	7.13	6.84	6.33	4.71 [5.13]***
$\hat{F}_2^{ALL}$	10.81	12.25	12.82	10.29	11.10	-0.29 [-0.27]
$\hat{F}_3^{ALL}$	21.05	21.16	19.84	21.91	21.33	-0.28 [-0.21]
$\hat{F}_4^{ALL}$	8.22	10.98	13.34	13.63	12.77	-4.55 [-5.49]***
$\hat{F}_{AVG}^{ALL}$	12.65	17.92	18.00	18.13	17.54	-4.89 [-4.04]***
R_{ALL}^2	2.95	2.90	2.67	2.76	2.41	0.54 [6.84]***

Table 3 shows the liquidity-sorted estimate coefficients based on the principal component predictive regression results of equation (1). All of the positive and significant of estimate coefficients are sorted into five groups based on each firm's aggregate illiquidity ranking. We apply Amihud's (2002) illiquidity proxy by calculating the monthly illiquidity index from the changes in absolute daily returns for a given trading volume. The proportions for the lowest liquidity firms (L) to the highest liquidity firms (H) in the second to sixth columns show that macroeconomic variables in panel A have stronger predictive power for high liquidity firms while technical indicators in panel B display higher predictive ability for low liquidity firms. Moreover, the first principal component of PC-ALL model in panel C shows similar predictive information of technical variables in panel B while the rest three principal components display identical forecast information of macroeconomic variables in panel A. The average R^2- statistic of all the firms for each model report in the last row of each panel, which is larger in magnitude for low liquidity firms. The proportions difference between highest liquidity and lowest liquidity firm shows in the last column of table 2 and the corresponding t-value inside the bracket come from the estimate 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 positive and significant dummy variable, if the estimated coefficient of each firm is positive and significant at the 10% level then D_{PS} equal to the unit, otherwise zero. D_i is the dummy variable of individual firm's liquidity group. For example, if a firm in the highest liquidity group, D_1 equals to the unit, otherwise zero. The t-statistic of the difference average R^2- statistic between the highest and lowest liquidity firms is also calculated by the equation above with replacement of the D_{PS} to the R^2- statistic from the regression of equation (1).

Table 4: Volatility-Sorted Principal Component Predictive Regression Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Positive and Significant Proportion						
Component	H (High Volatility)	2	3	4	L (Low Volatility)	H-L [t-stat]
Panel A: Macroeconomic variables						
$\hat{F}_1^{ECON}$	8.68	8.11	9.72	8.28	6.79	1.89 [2.03]**
$\hat{F}_2^{ECON}$	16.50	17.83	23.52	24.84	26.68	-10.18 [-7.29]***
$\hat{F}_3^{ECON}$	9.60	9.09	12.71	15.41	17.37	-7.77 [-6.87]***
$\hat{F}_{AVG}^{ECON}$	11.60	11.67	15.32	16.18	16.95	-5.35 [-2.95]***
R_{ECON}^2	2.22	2.08	2.34	2.31	2.16	0.06 [0.86]
Panel B: Technical variables						
$\hat{F}_1^{TECH}$	10.93	9.72	9.55	7.48	7.30	3.63 [3.74]***
R_{TECH}^2	0.65	0.61	0.58	0.50	0.49	0.16 [5.70]***
Panel C: All predictors						
$\hat{F}_1^{ALL}$	8.86	8.11	8.05	6.90	8.11	0.75 [0.81]
$\hat{F}_2^{ALL}$	13.63	10.70	13.46	11.39	8.11	5.52 [5.12]***
$\hat{F}_3^{ALL}$	16.56	18.29	22.02	22.89	25.53	-8.97 [-6.51]***
$\hat{F}_4^{ALL}$	6.21	9.49	14.72	14.84	13.69	-7.48 [-4.98]***
$\hat{F}_{AVG}^{ALL}$	11.85	16.10	19.26	18.65	18.56	-6.71 [-3.99]***
R_{ALL}^2	2.87	2.74	2.87	2.71	2.49	0.38 [4.70]***

Table 4 shows the volatility-sorted estimate coefficients based on the principal component predictive regression results of equation (1). All positive and significant principal component estimate coefficients sort into five groups based on each firm's volatility ranking. We estimate the firm's monthly volatility by the standard deviation of daily return of each firm. The positive and significant proportion of estimated coefficients from the highest volatility firms (H) to the lowest volatility firms (L) report in the second to sixth columns and the volatility-sorted average R^2 report in the last row of each panel. Macroeconomic variables in panel A have stronger predictive power for low volatility firms while technical indicators in panel B display higher predictive ability for highest volatility firms. Moreover, the first principal component of PC-ALL model in panel C show similar predictive information of technical variables in panel B while the other three principal components display close identical forecast information of macroeconomic variables in panel A. The difference of positive and significant (PS) proportions between highest and lowest volatility firms shows in the last column of table 4 and the corresponding t-value inside the bracket come from the estimate 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} represent the dummy variable if prediction result of each firm is positive and significant at the 10% level then D_{PS} equal to unit, otherwise zero. D_i is the dummy variable of each volatility group. For example, if a firm in the highest volatility group D_1 equals to the unit, otherwise zero. The t-statistic of the difference average R^2 statistic between the highest and lowest volatility firms is also calculated by the equation above with replacement of the D_{PS} to the R^2- statistic from the regression of equation (1).

Table 5: Principal Component Predictive Regression Results across Business Cycle

(1)	(2)	(3)	(4)	(5)	(6) [(2) - (3)]	(7) [(4) - (5)]	(8) [(2) - (4)]	(9)
	REC (β_n)		EXP (γ_n)		$PS^R - NS^R$	$PS^E - NS^E$	$PS^R - PS^E$	$R^2(\%)$
Predictor	PS	NS	PS	NS	[t-stat]	[t-stat]	[t-stat]	
Panel A: Macroeconomic variables								
$\hat{F}_1^{ECON}$	5.66	6.14	11.95	2.07	-0.48 [-0.33]	9.88 [6.75]***	-6.29 [-4.34]***	4.17
$\hat{F}_2^{ECON}$	23.22	3.81	14.94	2.28	19.41 [13.76]***	12.66 [8.73]***	8.28 [6.07]***	
$\hat{F}_3^{ECON}$	15.17	6.36	8.80	3.57	8.81 [6.15]***	5.23 [3.56]***	6.37 [4.48]***	
$\hat{F}_{AVG}^{ECON}$	14.68	5.43	11.90	2.64	9.25 [11.13]***	9.26 [10.98]***	2.79 [3.42]***	
Panel B: Technical variables								
$\hat{F}_1^{TECH}$	10.39	1.28	4.57	3.85	9.11 [6.19]***	0.71 [0.48]	5.82 [3.99]***	1.11
Panel C: All predictors								
$\hat{F}_1^{ALL}$	14.61	4.35	3.59	6.00	10.26 [7.11]***	-2.42 [-1.63]	11.02 [7.62]***	5.18
$\hat{F}_2^{ALL}$	8.60	4.74	13.24	1.91	3.86 [2.64]***	11.33 [7.77]***	-4.63 [-3.99]***	
$\hat{F}_3^{ALL}$	19.08	6.05	15.07	2.63	13.03 [9.12]***	12.43 [8.59]***	4.01 [2.99]***	
$\hat{F}_4^{ALL}$	16.18	5.37	9.78	3.01	10.81 [7.55]***	6.76 [4.61]***	6.41 [4.53]***	
$\hat{F}_{AVG}^{ALL}$	14.62	5.13	10.42	3.39	9.49 [13.18]***	7.03 [9.60]***	4.20 [5.92]***	
							$R_{ALL}^2 - R_{ECON}^2$	1.01 [51.07]***
							$R_{ALL}^2 - R_{TECH}^2$	4.06 [119.21]***

Table 5 reports firm level predictability results across business cycle the by equation 3 as follow:

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{P} * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^{P} * DEXP_t + \varepsilon_{t+1}, \quad (3)$$

where $DREC_t$ ($DEXP_t$) is the NBER recession (expansion) dummy variable that equals to unity when month t in recession (expansion) and zero otherwise, $DEXP_t = 1 - DREC_t$. The second (fourth) column shows the positive and significant proportion of estimate slope β_n (γ_n) during the recession (expansion) while the negative and significant proportions for recession and expansion are reported on the third and fifth column respectively. The six and seventh columns show that the positive proportions are significantly higher than the negative and significant proportion for all the three principal component analysis (PCA) across business cycle while column (8) indicates that all the principal component predictors have better performance during the recession.

Table 6: Size-Sorted PCA Results across Business Cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession				Expansion		$(S-L)^R-(S-L)^E$
	S	L	$(S-L)^R$[t-stat]	S	L	$(S-L)^E$ [t-stat]	[F-Stat]
Panel A: Macroeconomic variables							
$\hat{F}_1^{ECON}$	4.89	5.74	-0.85 [-1.09]	10.47	8.61	1.86 [1.69]*	-2.71 [4.09]**
$\hat{F}_2^{ECON}$	20.01	22.04	-2.03 [-1.42]	15.76	12.86	2.90 [2.40]***	-4.93 [7.45]***
$\hat{F}_3^{ECON}$	11.90	19.75	-7.85 [-6.47]***	6.27	10.91	-4.64 [-4.84]***	-3.21 [4.79]**
$\hat{F}_{AVG}^{ECON}$	12.27	15.84	-3.58 [-1.97]**	10.83	10.79	0.04 [0.02]	-3.62
R^2_{ECON}	4.28	3.36	0.92 [8.14]***				
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	11.56	9.87	1.69 [1.63]	8.05	2.24	5.81 [8.25]***	-4.12 [10.80]***
R^2_{TECH}	1.17	0.90	0.27 [6.03]***				
Panel C: All predictors							
$\hat{F}_1^{ALL}$	15.35	14.81	0.54 [0.45]	6.27	2.30	3.97 [6.32]***	-3.43 [6.39]**
$\hat{F}_2^{ALL}$	7.65	10.62	-2.97 [-3.13]***	13.23	8.67	4.56 [3.98]***	-7.53 [25.15]***
$\hat{F}_3^{ALL}$	18.29	20.09	-1.80 [-1.36]	15.58	14.12	1.46 [1.21]	-3.26 [3.51]*
$\hat{F}_4^{ALL}$	12.82	21.13	-8.31 [-6.67]***	8.86	10.22	-1.36 [-1.35]	-6.95 [19.92]***
$\hat{F}_{AVG}^{ALL}$	13.53	16.66	-3.13 [-2.01]**	10.98	8.83	2.16 [1.34]	-5.29
R^2_{ALL}	5.36	4.17	1.19 [9.65]***				

Table 6 shows the size-sorted principal component predictive regression results across the business cycle of equation (3). The t-values inside the bracket immediate beside the proportion difference of smallest and largest size firms are calculated from the t-statistic of α_1 by 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, if the estimated coefficient of each firm is positive and significant at the 10% level then D_{PS} equal to the unit, otherwise zero. We report the positive and significant proportions of slope coefficients for smallest firms (largest firms) during recession and expansion in the second (third) and fifth (sixth) columns respectively. Macroeconomic variables in panel A exhibit stronger predictive power for large firms while technical variables in panel B can better predict smaller firms during expansion. The first principal component in panel C reflects nearly similar predictive information of technical variables in panel B while the other three principal components display similar predictive ability of macroeconomic predictors in panel A. The R^2 statistic in the last row of each panel shows that the R^2- statistic for the PC-ALL model general equals the sum of the R^2- statistics for the PC-MACRO and PC-TECH models.

Table 7: Liquidity-Sorted PCA Results across Business Cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession				Expansion		$(L-H)^R-(L-H)^E$
	L	H	$(L-H)^R$[t-stat]	L	H	$(L-H)^E$ [t-stat]	[F-Stat]
Panel A: Macroeconomic variables							
$\hat{F}_1^{ECON}$	4.95	6.10	-1.15 [-1.47]	10.29	10.81	-0.52 [-0.47]	-0.63 [0.22]
$\hat{F}_2^{ECON}$	21.74	20.41	1.33 [0.92]	14.61	13.63	0.98 [0.81]	0.35 [0.04]
$\hat{F}_3^{ECON}$	11.62	17.42	-5.80 [-4.77]***	5.75	10.06	-4.31 [-4.50]***	-1.49 [1.04]
$\hat{F}_{AVG}^{ECON}$	12.77	14.64	-1.88 [-1.03]	10.22	11.50	-1.28 [-0.69]	-0.60
R_{ECON}^2	4.34	3.64	0.70 [6.43]***				
Panel B: Technical variables							
$\hat{F}_1^{TECH}$	11.16	8.97	2.19 [2.11]**	7.48	3.11	4.37 [6.19]***	-2.18 [3.02]*
R_{TECH}^2	1.20	0.99	0.21 [4.69]***				
Panel C: All predictors							
$\hat{F}_1^{ALL}$	13.68	14.09	-0.41 [-0.34]	5.64	2.76	2.88 [4.57]***	-3.29 [5.84]**
$\hat{F}_2^{ALL}$	7.48	9.55	-2.07 [-2.18]**	14.15	11.85	2.30 [2.00]**	-4.37 [8.43]***
$\hat{F}_3^{ALL}$	18.06	18.46	-0.40 [-0.30]	15.12	14.72	0.40 [0.33]	-0.80 [0.21]
$\hat{F}_4^{ALL}$	11.10	17.88	-6.78 [-5.45]***	6.96	10.01	-3.05 [-3.03]***	-3.73 [5.76]**
$\hat{F}_{AVG}^{ALL}$	12.58	14.99	-2.41 [-1.53]	10.47	9.83	0.64 [0.39]	-3.05
R_{ALL}^2	5.39	4.59	0.80 [6.44]***				

Table 7 shows the liquidity-sorted principal component predictive regression across business cycle of equation (3). The t-values inside the bracket immediate beside the proportion difference of lowest and highest liquidity firms are calculated from the t-statistic of α_1 by 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; if the estimated coefficient of each firm is positive and significant at the 10% level then D_{PS} equal to the unit, otherwise zero. We report the positive and significant proportions of slope coefficients for high illiquidity firms (high liquidity firms) during recession and expansion in the second (third) and fifth (sixth) columns respectively. Macroeconomic variables in panel A exhibit stronger predictive power for high liquidity firms while technical variables in panel B can better predict low liquidity firms during expansion. The first principal component in panel C reflects similar predictive information of technical variables in panel B while the other three principal components display close identical predictive ability of macroeconomic predictors in panel A. The R^2 statistic in the last row of each panel shows that the R^2- statistic for the PC-ALL model general equals the sum of the R^2- statistics for the PC-MACRO and PC-TECH models.

Table 8: Volatility-Sorted PCA Results across Business Cycle

(1)	(2)	(3)	(4) [(2)-(3)]	(5)	(6)	(7) [(5)-(6)]	(8) [(4)-(7)]
	Recession					Expansion	$(H-L)^R-(H-L)^E$
	H	L	$(H-L)^R$[t-stat]	H	L	$(H-L)^E$ [t-stat]	[F-Stat]
			Panel A: Macroeconomic variables				
$\hat{F}_1^{ECON}$	7.36	4.14	3.22 [4.12]***	12.36	8.34	4.02 [3.67]***	-0.80 [0.36]
$\hat{F}_2^{ECON}$	22.31	23.29	-0.98 [-0.68]	11.56	18.23	-6.67 [-5.63]***	5.69 [10.34]***
$\hat{F}_3^{ECON}$	14.38	16.50	-2.12 [-1.75]*	6.15	12.25	-6.10 [-6.36]***	3.98 [7.34]***
$\hat{F}_{AVG}^{ECON}$	14.68	14.64	0.04 [0.02]	10.02	12.98	-2.96 [-1.60]	3.00
R_{ECON}^2	4.25	3.88	0.37 [3.21]***				
			Panel B: Technical variables				
$\hat{F}_1^{TECH}$	9.83	10.70	-0.87 [-0.83]	7.13	2.59	4.54 [6.44]***	-5.41 [18.57]***
R_{TECH}^2	1.17	1.00	0.17 [3.92]***				
			Panel C: All predictors				
$\hat{F}_1^{ALL}$	12.48	15.99	-3.51 [-2.93]***	4.77	2.36	2.41 [3.83]***	-5.92 [19.09]***
$\hat{F}_2^{ALL}$	9.66	8.51	1.15 [1.21]	13.97	10.12	3.85 [3.36]***	-2.70 [3.23]***
$\hat{F}_3^{ALL}$	17.08	19.95	-2.87 [-2.16]**	12.02	18.69	-6.67 [-5.51]***	3.80 [4.73]***
$\hat{F}_4^{ALL}$	13.92	17.42	-3.50 [-2.81]***	7.88	10.01	-2.13 [-2.11]**	-1.37 [0.79]
$\hat{F}_{AVG}^{ALL}$	13.28	15.47	-2.19 [-1.39]	9.66	10.29	-0.63 [-0.39]	-1.56
R_{ALL}^2	5.37	4.73	0.64 [4.04]***				

Table 8 shows the volatility-sorted principal component analysis results across business cycle by equation (3). The t-value inside the bracket immediate beside the proportion difference between the highest volatility (H) and lowest volatility (L) firms calculate from the t-statistic of α_1 by 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 of positive and significant estimate coefficient. If the estimated coefficient is positive and significant at the 10% level then we define D_{PS} to the unit, otherwise zero. We report the proportion of positive and significant slope coefficients for the highest volatility (lowest volatility) firms during recession and expansion in the second (third) column and third (sixth) columns respectively. In panel A, the second and third principal components extracted from macroeconomic variables exhibit stronger predictive power for low volatility firms during expansion. However, technical indicators in panel B show higher forecast ability for volatile firms in the expansion. The first principal component in panel C shows similar predictive information of technical variables in panel B while the other three principal components display similar predictive ability of macroeconomic predictors in panel A. The R^2 statistic in the last row of each panel shows that the R^2- statistic for the PC-ALL model general equals the sum of the R^2- statistics for the PC-MACRO and PC-TECH models.

Appendix 1: Firm Level Prediction Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Macroeconomic variables					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]	8.76	2.35	6.42 [4.35]***	MA(1,9)	0.67 [1.78]**	10.30	2.01	8.29 [5.64]***
NTIS	0.66 [0.06]	12.25	4.75	7.50 [5.17]***	MA(1,12)	0.87 [2.22]**	12.13	1.75	10.39 [7.10]***
DP	0.78 [1.98]**	13.88	1.62	12.26 [8.42]***	MA(2,9)	0.70 [1.88]**	8.50	1.87	6.62 [4.49]***
EP	0.43 [0.97]	8.29	2.83	5.46 [3.71]***	MA(2,12)	0.94 [2.42]***	9.79	1.68	8.11 [5.51]***
DE	0.59 [0.93]	7.02	2.65	4.37 [2.95]***	MA(3,9)	0.77 [2.04]**	8.04	3.52	4.52 [3.07]***
TBL	0.11 [1.90]*	14.24	1.81	12.43 [8.55]***	MA(3,12)	0.54 [1.39]	4.43	3.81	0.62 [0.42]
LTY	0.08 [1.25]	8.18	3.73	4.45 [3.03]***	MOM(9)	0.55 [1.40]	6.46	2.15	4.31 [2.91]***
LTR	0.13 [2.05]**	21.15	1.84	19.31 [13.53]***	MOM(12)	0.58 [1.44]	5.15	2.53	2.62 [1.76]*
TMS	0.20 [1.74]*	16.93	1.24	15.69 [10.85]***	VOL(1,9)	0.68 [1.86]**	11.80	0.84	10.96 [7.47]***
DFY	0.16 [0.37]	17.75	1.73	16.02 [11.12]***	VOL(1,12)	0.89 [2.31]**	13.32	0.66	12.66 [8.66]***
DFR	0.16 [0.89]	10.25	1.83	8.42 [5.73]***	VOL(2,9)	0.74 [2.02]**	12.82	0.71	12.11 [8.27]***
DY	0.84 [2.13]**	19.10	0.99	18.11 [12.59]***	VOL(2,12)	0.74 [1.94]*	8.97	0.97	8.00 [5.41]***
INFL	0.10 [0.18]	11.27	4.50	6.77 [4.65]***	VOL(3,9)	0.48 [1.27]	5.84	2.33	3.51 [2.36]***
RVOL	7.39 [2.45]***	16.33	0.95	15.38 [10.61]***	VOL(3,12)	0.85 [2.25]**	7.02	2.08	4.93 [3.33]***

Appendix 1 report the predictive regression results of market and firm level respectively. Firm level proportion results of estimate coefficients β_i of all individual firms by following forecasting regression,

$$y_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \qquad (4)$$

where y_{t+1} is one of the 8,695 firms' log excess return at month t. $x_{i,t}$ presents one of the 14 macroeconomic variables or 14 technical indicators in column (1) and (6) respectively. Column (2) include the overall market predict results collected from Neely et al.'s (2014) paper. Column (3) – (4) shows individual level forecasting results by proportion with the same data spanning of Neely et al. (2014) from January 1951 to December 2011. The third (fourth) column represents positive (negative) and significant proportion of estimate results at the 10% level under Newey-West test. Column (5) indicate difference between positive and negative significant proportion. The insignificant predict results of overall market in second column indicate that both macroeconomic variables and technical indicators can hard predict market return. However, the all the higher positive and significant proportion showed in column (3) indicate that market level predictability actually shows up in the individual stocks, especially for the five macroeconomic indicators: LTR, TMS, DFY, DY and RVOL and the four technical variables: MA(1,3), VOL(1,9), VOL(1,12) and VOL(2,9).

Appendix 2: Size-Sorted Firm Level Predictive Regression Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Positive and Significant Proportion			
Predictor	S (Small)	2	3	4	L (Large)	S-L [t-stat]
			Panel A: Macroeconomic Variable			
BM	6.21	9.43	8.57	10.89	8.73	-2.52 [-2.63]***
NTIS	10.64	11.44	12.77	13.82	12.57	-1.93 [-1.74]*
DP	9.09	12.88	13.86	16.47	17.11	-8.02 [-6.87]***
EP	5.52	7.07	8.63	10.94	9.30	-3.78 [-4.05]***
DE	6.73	7.59	7.02	6.68	7.06	-0.33 [-0.38]
TBL	15.87	16.16	14.49	11.87	12.80	3.07 [2.59]***
LTY	9.26	9.72	8.11	7.32	6.49	2.77 [2.99]***
LTR	10.52	15.12	19.38	27.07	33.64	-23.12 [-17.05]***
TMS	15.41	17.54	19.03	17.22	15.44	-0.03 [-0.02]
DFY	14.15	18.46	17.83	20.68	17.62	-3.48 [-2.69]***
DFR	13.57	11.62	10.18	7.49	8.38	5.19 [5.06]***
DY	15.12	19.26	17.83	21.89	21.41	-6.29 [-4.73]***
INFL	14.55	15.64	10.81	9.56	5.80	8.75 [8.21]***
RVOL	11.73	14.66	16.22	18.61	20.44	-8.71 [-6.97]***
			Panel B: Technical Variable			
MA(1,9)	13.46	12.48	9.72	8.24	7.63	5.82 [5.66]***
MA(1,12)	15.35	14.09	10.58	9.91	10.73	4.62 [4.18]***
MA(2,9)	10.35	9.26	8.34	6.74	7.81	2.54 [2.69]***
MA(2,12)	9.78	11.04	9.20	8.35	10.56	-0.79 [-0.78]
MA(3,9)	8.51	9.20	7.19	6.97	8.32	0.19 [0.20]
MA(3,12)	5.12	5.46	3.97	3.28	4.31	0.81 [1.17]
MOM(9)	8.57	8.51	5.46	4.78	4.99	3.57 [4.30]***
MOM(12)	7.07	6.50	4.20	3.92	4.08	3.00 [4.01]***
VOL(1,9)	17.14	14.72	11.10	8.99	7.06	10.08 [9.27]***
VOL(1,12)	17.31	15.99	12.31	11.18	9.82	7.49 [6.53]***
VOL(2,9)	17.19	14.61	11.44	10.66	10.22	6.98 [6.17]***
VOL(2,12)	11.33	11.21	7.82	7.49	7.00	4.32 [4.47]***
VOL(3,9)	9.95	7.65	3.74	4.03	3.85	6.10 [7.72]***
VOL(3,12)	9.03	7.82	5.64	5.36	7.23	1.80 [2.08]**

Appendix 2 is the size-sorted firm's positive and significant proportion of estimate coefficients significant at the 10% level under Newey-West regression test. All the individual firms are sorted into five groups according to their aggregate size rank that calculated from average monthly size rank based on capitalization data. Column (2) – (6) report the positive and significant proportion of each size-sorted firm groups, S represent the smallest firms while L represent the largest firms. The last column of table 2 used to test the proportion difference between the smallest firm and largest firms, macroeconomic variable in general can better predict large firms, especially for the five macroeconomic indicators: DP, LTR, DY, INFL and RVOL. Technical indicators have a higher predict power in smaller firms, in addition, MA(1,9), VOL(1,9), VOL(2,9) and VOL(3,9) have significantly higher predict ability for smallest firms.

Appendix 3: Principal Component Predictive Regressions Results across Business Cycle (CFNAI_MA3: 1967:06-2011.12)

(1)	(2)	(3)	(4)	(5)	(6) [(2) - (3)]	(7) [(4) - (5)]	(8) [(2) - (4)]	(9) [(3) - (5)]	
	REC(β_K)		EXP(γ_K)		$PS^R - NS^R$	$PS^E - NS^E$	$PS^R - PS^E$	$NS^R - NS^E$	R^2(%)
Predictor	PS	NS	PS	NS	[t-stat]	[t-stat]	[t-stat]	[t-stat]	
Panel A: Macroeconomic Variable									
$\hat{F}_1^{ECON}$	12.41	3.13	7.49	3.61	9.27 [6.18]***	3.88 [2.56]***	4.92 [3.32]***	-0.48 [-0.31]	4.18
$\hat{F}_2^{ECON}$	14.66	4.16	20.07	2.11	10.50 [7.06]***	17.96 [12.19]***	-5.40 [-3.81]***	2.05 [1.33]	
$\hat{F}_3^{ECON}$	10.64	9.09	8.76	2.73	1.55 [1.05]	6.03 [3.97]***	1.88 [1.18]	6.36 [4.19]***	
Average	11.85	5.15	11.41	2.66	6.70 [8.00]***	8.76 [10.37]***	0.44 [0.53]	2.49 [2.90]***	
Panel B: Technical Variable									
$\hat{F}_1^{TECH}$	9.31	2.26	4.67	2.49	7.05 [4.65]***	2.18 [1.42]	4.64 [3.08]***	-0.23 [-0.15]	1.09
Panel C: All Variable									
$\hat{F}_1^{ALL}$	13.93	3.20	4.31	3.48	10.73 [7.19]***	0.83 [0.54]	9.62 [6.46]***	-0.28 [-0.13]	5.34
$\hat{F}_2^{ALL}$	20.30	3.35	8.43	2.94	16.94 [11.55]***	5.49 [3.62]***	11.87 [8.21]***	0.41 [0.27]	
$\hat{F}_3^{ALL}$	13.45	5.92	19.63	2.60	7.54 [5.08]***	17.03 [11.56]***	-6.17 [-4.32]***	3.32 [2.17]**	
$\hat{F}_4^{ALL}$	12.75	6.68	10.33	3.10	6.06 [4.08]***	7.23 [4.79]***	2.42 [1.64]*	3.59 [2.35]**	
Average	14.24	4.51	10.06	1.66	9.73 [13.48]***	7.21 [9.83]***	4.18 [5.88]***	1.66 [2.23]***	
								$R^2(\hat{F}^{ALL}) - R^2(\hat{F}^{ECON})$	1.16 [55.27]***
								$R^2(\hat{F}^{ALL}) - R^2(\hat{F}^{TECH})$	4.25 [119.17]***

Appendix 3 reports firm level predictability results across business cycle by following regression,

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \hat{F}_{n,t}^{N} * DREC_t + \sum_{n=1}^{N} \gamma_n \hat{F}_{n,t}^{N} * DEXP_t + \varepsilon_{t+1} \qquad (3)$$

where y_{t+1} is the risk premium return of each firm while $\hat{F}_{n,t}^{N}$ represent the Kth principal component we abstract from the 14 fundamental variables, 14 technical predictors, or all the 28 predictors together. We apply CFNAI_MA3 index to calculate the recession and expansion dummy indicators and the data spanning cut by CFNAI_MA3 index from Jun 1967 to December 2011. $DREC_t(DEXP_t)$ equal to unity if CFNAI_MA3 is less (higher) than -0.7 and zero otherwise. The second (fourth) column presents the positive and significant proportion of estimate slope β_n (γ_n). The third (fifth) column shows the negative and significant proportion during recession (expansion). The t-value inside the bracket immediate beside the proportion difference between the smallest and largest firm calculate from the t-statistic of α_1 by the following linear regression:

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