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Are individual stock returns predictable?

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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 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.

JEL Classification: **C58, E32, G11, G12, G17**

Keywords
Business cycle, cross-sectional predictability, firm-level predictability, limits to arbitrage, macroeconomic and technical predictors, principal component analysis

1. Introduction

Macroeconomic variables and technical indicators are predictors of market-level equity returns (e.g. Brock et al., 1992; Goyal and Welch, 2008). Neely et al. (2014; NRTZ hereafter) show that

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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 et al. (2011) find that the implied cost of capital (ICC) estimates are significantly correlated to future returns. Christensen et al. (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 ICC. 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 macrovariables, 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 article 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.

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 et al. (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 et al., 2008; 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 et al., 1998; Hong and Stein, 1999), and asset allocation (Zhu and Zhou, 2009).

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 et al. (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 et al. (2001) find that investors bear higher idiosyncratic risk by investing in individual stocks rather than the aggregate market. Stambaugh et al. (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, that is, 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, that is, 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 et al. (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 perform comparatively better in recessions whereas technical indicators perform similarly across the economic states. When 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 article proceeds as follows. Section 2 presents the data and method. Empirical results are discussed in Section 3. Finally, Section 4 concludes the article.

2. Data and method

2.1. 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 website[4] 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.

2.2. Method

2.2.1. Principal component predictive regression. We apply the principal component predictive regression in detecting the predictability of individual stocks as follows

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

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; $\widehat{F}_{n,t}^{P}$ represents the nth principal component which incorporates information from the documented 14 fundamental variables (P=MACRO), 14 technical predictors (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 $H_0 : \beta_n = 0$ against $H_A : \beta_n \neq 0$. 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. First, we create a bootstrapped predictor $(\widehat{F}_t^{B})$ 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 PS 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 PS proportions of the bootstrapped predictor to calculate the p-value of the proportion of PS results for each of the predictors.

PCA is the most commonly used tool in financial studies for parsimoniously incorporating information from a large group of predictors in the predictive regression (e.g. Ludvigson and Ng, 2007; Zhu, 2014). 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 (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 PCA in equation (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 follows

$$y_{t+1} = \alpha_i + \beta_i x_{j,t} + \varepsilon_{j,t+1} \tag{2}$$

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. Finally, the firm's illiquidity index is Amihud's (2002) illiquidity measure calculated as follows

$$ILLIQ_t = 10^6 \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_t|}{DVOL_t} \tag{3}$$

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

$$y_{t+1} = \alpha + \sum_{n=1}^{N} \beta_n \widehat{F}^{P}_{n,t} \times DREC_t + \sum_{n=1}^{N} \gamma_n \widehat{F}^{P}_{n,t} \times DEXP_t + \varepsilon_{t+1} \tag{4}$$

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 3-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.

2.2.2. 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 PS estimated coefficients and apply the following linear regression

$$D_{ps} = a_0 + a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4 D_4 + \varepsilon \tag{5}$$

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

2.2.3. 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 (1) and compute the forecasted stock return for the following month based on past 120-month observations. Second, we rank all the securities into 10 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 1 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.

3. Empirical results

3.1. Firm-level predictability evidence

Table 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.

The last column in Table 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.

Appendix 1 shows that the conventional bivariate predictive regression results are robust to the principal component predictive analysis (PCA) in Table 1. All the macroeconomic variables and

Table 1. Firm-level principal component predictive regression.

(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]***		
			$R^2_{ALL} - R^2_{MACRO}$			0.46 [22.93]***	−0.18 [–8.71]***
			$R^2_{ALL} - R^2_{TECH}$			2.13 [87.60]***	0.54 [24.10]***

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

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

where y_{t+1} represents the market-level or individual firm level's natural logarithm of equity risk premium respectively. $\hat{F}^P_{n,t}$ 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) indicate significance at the 10%, 5%, and 1% levels, respectively, according to one-sided (upper-tail) wild bootstrapped *p*-values; ***, **, and * in the rest of the columns indicate statistical significance at the 1%, 5%, and 10% levels, respectively. To illustrate the firm-level results, we group the estimated coefficients, associated with each of the principal components and significance 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 9 out of 10 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.

most of the 14 technical variables exhibit significantly predictive power in forecasting individual firm returns. Macroeconomic variables: LTR, DMS, and DY exhibit impressively predictive ability among all the predictors in the univariate predictive regression. Besides, Appendix 2 illustrates that

Table 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]***

Table 2 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 10 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 1 month. After getting the monthly average returns, we calculate the risk-adjusted returns by the Carhart four-factor model. *** indicate statistical significance at the 1% level.
WML is the difference between the average returns of the Winner and Loser portfolios. SMB (Small minus Big) is the average return on the small portfolio minus the average return on the big portfolio. HML (High minus Low) is the average return on the value portfolio minus the average return on the growth portfolio. MKT is the excess return on the market. MOM is the average return on the high prior return portfolio minus the average return on the low prior return portfolio.

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 1, which further confirms the complementary role of macroeconomic and technical predictors displayed in predicting individual stock returns.

In Table 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.

3.2. 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. Li and Zhang, 2010; Whited and Wu, 2006). 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

Table 3. Size-sorted principal component predictive regression results.

(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^2_{MACRO}	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^2_{TECH}	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^2_{ALL}	3.34	3.00	2.74	2.61	2.05	1.29 [14.52]***

Table 3 shows the size-sorted estimate coefficients based on the principal component predictive regression results of equation (1) (see Table 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 (1). *** and * indicate statistical significance at the 1% and 10% level, respectively.

arbitrage risk (measured by volatility), transaction costs (measured by Amihud (2002) illiquidity), and the investment friction (measured by firm size). We keep all the 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.

Table 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 ($\widehat{F}_1^{ALL}$, $\widehat{F}_2^{ALL}$) 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 ($\widehat{F}_1^{ALL}$) for the PC-ALL model in Panel C are similar to that of the principal component ($\widehat{F}_1^{TECH}$) of the PC-TECH model in Panel B. However, the third principal component ($\widehat{F}_3^{ALL}$) of the PC-ALL model in Panel C performs more similar to the third principal component ($\widehat{F}_3^{MACRO}$) of the PC-MACRO model in Panel A.

NRTZ (2014) shows that $\widehat{F}_1^{ALL}$ behaves very similar to $\widehat{F}_1^{TECH}$ 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 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. In addition, 11 of the 12 average R^2-statistics are above the 0.5% threshold.

Moreover, the results in Appendix 3 deliver the same information as Table 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 PS 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 4 exhibit a similar predictive pattern to the size-sorted findings in Table 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 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

Table 4. Liquidity-sorted principal component predictive regression results.

(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^2_{MACRO}	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^2_{TECH}	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^2_{ALL}	3.03	3.05	2.81	2.71	2.13	0.90 [10.03]***

Table 4 shows the liquidity-sorted estimate coefficients based on the principal component predictive regression results of equation (1) (see Table 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

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

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 (1). *** indicate statistical significance at the 1% level.

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 $(\widehat{F}_1^{ALL})$ reports identical predictive information in forecasting low liquidity firms as the technical component in Panel B.

Table 5. Volatility-sorted principal component predictive regression results.

(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]***

Table 5 shows the volatility-sorted estimate coefficients based on the principal component predictive regression results of equation (1) (see Table 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

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

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% and 5% levels, respectively.

However, the third component ($\widehat{F}_3^{ALL}$) 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 3 and further supports the complementary prediction evidence of macroeconomic variables and technical indicators in predicting liquidity-sorted individual stocks.

The volatility-sorted proportion results in Table 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, $\widehat{F}_2^{MARCO}$ and $\widehat{F}_3^{MACRO}$, together with the average proportion for the three principal components, $\widehat{F}_{AVG}^{MARCO}$, all generate significantly higher PS proportions (9.42%, 6.49%, and 4.56% respectively) in forecasting the low-volatility firms. However, Panel B shows that the magnitude of the PS proportions in the PC-TECH model significantly reduces with the decrease in 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 PS 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 in volatility at the end of each panel, and 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 Tables 3 to 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 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 provide significant complementary evidence for macroeconomic and technical predictors in providing complementary predictive information to equity return prediction. Panel A of Table 6 shows that DP, DY, and BM load most heavily on the first principal component ($\widehat{F}_1^{MACRO}$) extracted from the 14 macroeconomic variables. They have the highest average principal scores and positively load on the $\widehat{F}_1^{MACRO}$ over 95% of the principal component predictive regressions. Technical indicators in Panel B of Table 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, $\widehat{F}_1^{TECH}$.

Table 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

(Continued)

Table 6. (Continued)

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
Panel C: PC-ALL											
$\hat{F}_1^{ALL}$			$\hat{F}_2^{ALL}$			$\hat{F}_3^{ALL}$			$\hat{F}_4^{ALL}$		
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

(Continued)

Table 6. (Continued)

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

Table 6 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. 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 $\left(\hat{F}_1^{ALL}\right)$. 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.

PEC is the positive proportion for each variable to get the positive scores in all the regression. ASCORE is average principal component scores of each variable. DP is the dividend price ratio which is the difference between the log of dividends and the log of prices. DY is the dividend yield which is the difference between the log of dividends and the log of lagged prices. DFY is the default yield spread which is the difference between BAA and AAA-rated corporate bond yields. MOM is the price momentum. INFL is the inflation from the consumer price index (all urban consumers). MA is the moving average. BM is the book to market ratio for the Dow Jones Industrial Average. TBL is the Treasury-bill rates. TMS is the term spread which is the difference between the long term yield on the government bonds and the Treasury-bill. RVOL is the equity risk premium volatility. LTR is the long term rate of returns. NTIS is the net equity expansion which is the ratio of 12-month moving sums of the net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. DE is the dividend payout ratio which is the difference between the log of dividends and the log of earnings. DFR is the default return spread which is the difference between long-term corporate bond and long-term government bond returns. EP is the earnings price ratio which is the difference between the log of earnings and the log of prices. LTY is the long term government bond yield.

3.3. 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 7 report the overall predictability of individual stock returns across the business cycle. Columns 2–5 report the proportions of PS coefficients and NS coefficients under recession and expansion periods separately. Column 6 (7) shows the proportion of differences between PS and NS and their *t*-statistics for the recession (expansion) period. Column 8 reports the PS differences between recession and expansion periods.

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 equation (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 7.

3.4. 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 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 PS 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 PS 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

Table 7. Principal component predictive regression results across business cycle.

(1)	(2)	(3)	(4)	(5)	(6) ((2) − (3))	(7) ((4) − (5))	(8) ((2) − (4))	(9)
P.C.	REC (β_n)		EXP (γ_n)		$PS^R - NS^R$ [*t*-stat]	$PS^E - NS^E$ [*t*-stat]	$PS^R - PS^E$ [*t*-stat]	R^2(%)
	PS	NS	PS	NS				
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]***	
							$R^2_{ALL} - R^2_{MACRO}$	1.58 [29.03]***
							$R^2_{ALL} - R^2_{TECH}$	4.55 [94.78]***

Table 7 reports firm-level predictability results across the business cycle using the following equation

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

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. 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 6 and 7. In column 8, 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 8 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.

complementarity evidence. The difference between small and large firms' predictability is 2.15% significantly larger during recessions for the first principal component, $\widehat{F}_1^{ALL}$, whereas that difference is −2.55% and −3.34% significantly smaller during recessions for the second and fourth principal components, $\widehat{F}_2^{ALL}$ and $\widehat{F}_4^{ALL}$, associated with the macroeconomic

Table 8. Size-sorted PCA results across business cycle.

(1)	(2)	(3)	(4) ((2) − (3))	(5)	(6)	(7) ((5) − (6))	(8) ((4) − (7))
P.C.	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							
$\hat{F}_1^{MACRO}$	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]***				

PCA: principal component analysis.
Table 8 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

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

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% and 10% levels, respectively.

predictors. Smaller firms have significantly higher R^2 in the prediction regression than large firms in all three panels.

Table 9 shows the PCA 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 PS proportion for high-liquidity firms is at least 2.79% higher than that for low-liquidity

Table 9. Liquidity-sorted PCA results across business cycle.

(1)	(2)	(3)	(4) ((2) − (3))	(5)	(6)	(7) ((5) − (6))	(8) ((4) − (7))
P.C.	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							
$\hat{F}_1^{MACRO}$	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]***				

PCA: principal component analysis.

Table 9 shows the liquidity-sorted principal component predictive regression 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 lowest (L) and highest (H) liquidity firms and calculated from α_1 in the following linear regression

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

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. 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. 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, that is, recessions.

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

Table 10. Volatility-sorted PCA results across business cycle.

(1)	(2)	(3)	(4) ((2) − (3))	(5)	(6)	(7) ((5) − (6))	(8) ((4) − (7))
P.C.	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							
$\hat{F}_1^{MACRO}$	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]***				

PCA: principal component analysis.
Table 10 shows the volatility-sorted principal component analysis results across the business cycle by equation (4) (see Table 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

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

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.

liquidity firms' predictability confirms that both macroeconomic and technical indicators possess stronger predictive power in recession, as shown in Column 8.

Table 10 presents the results of volatility-sorted PCA 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.

4. Conclusion

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.

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).

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Notes

1. While the majority of papers consider predictability using market returns, many authors (including Jegadeesh and Titman, 2001; Lee and Swaminathan, 2000, for technical factors; and Boudoukh et al., 2007, and Mookerjee and Yu, 1997, for fundamental factors) have considered individual stock returns.
2. Chan et al. (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 et al. (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 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.
4. We thank Amit Goyal for making these data available on his website.
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.
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.

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Appendix 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]

Appendix 1 shows the market- and firm-level bivariate estimation results 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 *j*th 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.

BM is the book to market ratio for the Dow Jones Industrial Average. MA is the moving average. NTIS is the net equity expansion which is the ratio of 12-month moving sums of the net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. DP is the dividend price ratio which is the difference between the log of dividends and the log of prices. EP is the earnings price ratio which is the difference between the log of earnings and the log of prices. DE is the dividend payout ratio which is the difference between the log of dividends and the log of earnings. TBL is the Treasury-bill rates. TMS is the term spread which is the difference between the long term yield on the government bonds and the Treasury-bill. LTY is the long term government bond yield. MOM is the price momentum. LTR is the long term rate of returns. TMS is the term spread. VOL is the trading volume. DFY is the default yield spread which is the difference between BAA and AAA-rated corporate bond yields. DFR is the default return spread which is the difference between long-term corporate bond and long-term government bond returns. DY is the dividend yield which is the difference between the log of dividends and the log of lagged prices. INFL is the inflation from the consumer price index (all urban consumers). RVOL is the equity risk premium volatility.

Appendix 2. Firm-level principal component predictive regression (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]***		
				$R^2_{ALL} - R^2_{MACRO}$		0.52 [38.50]***	0.03 [2.45]**
				$R^2_{ALL} - R^2_{TECH}$		2.17 [97.23]***	0.73 [33.77]***

Appendix 2 shows principal component analysis (PCA) results at market and firm level based on the following regression

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

where y_{t+1} represents the market-level or individual firm level's log equity risk premium. $\hat{F}^P_{n,t}$ 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.

Appendix 3. Size-sorted principal component predictive regression results (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]***

Appendix 3 shows the size-sorted estimate coefficients based on the principal component predictive regression results of equation (1) for the period between January 1951 and 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

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

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.

Appendix 4. Principal component predictive regression results across business cycle (1967.06–2018.12)_CFNAI.

(1)	(2)	(3)	(4)	(5)	(6) ((2) − (3))	(7) ((4) − (5))	(8) ((2) − (4))	(9)
Predictor	REC (β_n)		EXP (γ_n)		$PS^R - NS^R$ [t-stat]	$PS^E - NS^E$ [t-stat]	$PS^R - PS^E$ [t-stat]	R^2(%)
	PS	NS	PS	NS				
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]***	4.71
$\hat{F}_2^{MACRO}$	16.22	4.23	19.03	2.33	11.99 [8.72]***	16.69 [12.18]***	−2.81 [−2.12]**	
$\hat{F}_3^{MACRO}$	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]*	6.34
$\hat{F}_2^{ALL}$	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]***	
$\hat{F}_4^{ALL}$	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]***	
							$R^2_{ALL} - R^2_{MACRO}$	1.63 [23.33]***
							$R^2_{ALL} - R^2_{TECH}$	4.82 [74.89]***

Appendix 4 reports firm-level predictability results across the business cycle using the following equation

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

where y_{t+1} represents the market-level or individual firm level's log equity risk premium. $\hat{F}_{n,t}^P$ is the nth 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.