Literature Review and Replication of "Investor Attention, Psychological Anchors, and Stock Return Predictability"

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I. LITERATURE REVIEW

1. Research question and hypotheses

The main research question of this paper is: Do the nearness to the 52-week high and the nearness to the historical high, because of psychology anchoring and limited investor attention, predict the future aggregate market returns? The goal of the research is to test whether the nearness to the 52-week high is a representation of underreaction, and the nearness to the historical high is a representation of overreaction of the market. The authors use various time-series regression, Monte Carlo simulations, international data from G7 countries ,along with cross-sectional regression to test for the robustness of the results.

While the authors do not explicitly state their hypotheses, the study is based on behavioral finance and previous empirical findings of psychology anchoring and limited investor attention. The implicit hypotheses are that, suggested by George and Hwang (2004), nearness to the 52-week high predicts positive future returns because investors underreact to positive news. In contrast, the nearness to historical high indicates negative future returns because when the market is far below its historical high, it suggests a prolonged period of bad news and when the market in proximity to the all-time peak, the traders might overreact due to excess of confidence and high levels of risk willingness (anchoring effect). In addition, one other hypothesis is that, because of limited investor attention, pointed out by Peng and Xiong (2006), investors tend to react to broad market information instead of firm-specific information. This is why the authors choose the Dow Jones index, with its availability and well-recognition, to capture the market-wide information instead of the broader NYSE/AMEX market capitalization index. Finally, the authors believe that the two psychological predictors, nearness to 52-week high and nearness to historical high, will predict market returns better than traditional economic variables such as default premium, term spread, or consumption-wealth ratio.

2. Data and methodology

2.1 Data

The main data is the Dow Jones Industrial Average index acquired on Dow Jones and the market broad data is NYSE/AMEX value-weighted returns from the Center for Research in Security Prices (CRSP). The excess returns are calculated by deducting the value-weighted returns by the 30-day Treasury Bill rate. The default premium (def_t) is the difference in yield between BAA and AAA bonds; the term premium ($term_t$) is the difference between 20-year and 1-year Treasury bond yields; the inflation rate is derived from monthly Consumer Price Index data from CRSP; the consumption-wealth ratio (cay_t) is taken from Lettau & Ludvigson; the surplus ratio (s_t) is based on Campbell & Cochrane (1999) and computed as a 40-quarter moving average of consumption growth (following Wachter, 2006); and the dividend yield (dp_t) is calculated by subtracting the log of the last 12-month dividend by the log of the CRSP value-weighted index. The data is mainly from 1958 to 2009. In addition, the authors expand their analysis to G7 countries to check the global robustness of the two proxies. The nearness to the 52-week high (x_{52}) is calculated by dividing the current Down index by its 52-week high to measure how close the index is to its highest level in the past year. The nearness to the historical high (x_{max}) is the current Dow index divided by its historical high to measure how close the index is to its all-time peak. Furthermore, the variable D_t equals 1 if the Dow index is at its historical high that day, 0 otherwise. The variable I_t equals 1 if its historical high equals its 52-week high that day, 0 otherwise.

2.2 Methodology

First, to get an overview of the data, the paper summarizes the mean, standard deviation, autocorrelation, skewness, and kurtosis of all the variables. Second, the primary method includes regressing future aggregate market returns on the proposed predictors while controlling for traditional macroeconomic variables with overlapping monthly regressions. Specifically, the Newey–West t-statistics for robustness is used to account for the autocorrelation and heteroskedasticity. In addition, the NYSE/AMEX is also used instead of the Dow Jones index to test if the limited investor's attention is valid. The paper also uses subsample analyses to test whether the findings are consistent across different periods. Third, a series of Monte Carlo simulations are conducted to test for robustnesss as the Newey–West t-statistics may suffer from small sample bias. In addition, they also test for spurious predictability by reordering the Dow index, for volatility clustering by VAR(1) and VAR-GARCH(1,1) models. Fourth, to test whether the two main predictive variables are constant across the world, the authors use data from the G7 countries' well-known indexes. Finally, the research uses cross-sectional analysis of stock returns to test the effects on individual stocks. The stocks are put into different quintiles based on different values to test for the momentum strategy and the value investing strategy.

While the authors rely on well-established stock market data and macroeconomic variables, their approach is novel in several ways. First, instead of testing for individual stock returns as many papers have before, the authors try to predict aggregate market returns, not only of US market but also of global markets, with two new predictive psychology variables. Second, to strengthen the results of their research, the paper uses extensive Monte Carlo simulations to test for small sample bias, out-of-sample predictability,... The paper succeeds in demonstrating that psychological anchoring effects extend beyond individual stocks to aggregate market returns and are robust across global markets.

3. Main result

3.1 Time series regression

Table 2
Monthly overlapping regression.

In this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted excess return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, and Dow 52-week high equal-historical high indicator I_t. We use overlapped monthly sampled data. The Newey–West t-stats given in parentheses control for heteroskedasticity and autocorrelation. Our sample is monthly from 1958.01 to 2009.12.

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	R^2
1-Month	0.09					0.01
	(1.82)					
3-Month	0.08					0.01
	(1.10)					
6-Month	−0.05					0.00
	(−0.53)					
1-Year	−0.16					0.02
	(−1.51)					
1-Month	0.12		−0.05			0.02
	(2.35)		(−2.15)			
3-Month	0.16		−0.18			0.04
	(2.49)		(−3.30)			
6-Month	0.14		−0.37			0.06
	(1.63)		(−3.69)			
1-Year	0.05		−0.52			0.07
	(0.37)		(−2.68)			
1-Month	0.11	0.10	−0.15	−0.49	0.93	0.03
	(2.06)	(1.86)	(−3.19)	(−0.73)	(2.01)	
3-Month	0.13	0.32	−0.48	−1.29	3.20	0.07
	(1.96)	(2.09)	(−3.79)	(−0.97)	(2.55)	
6-Month	0.07	0.60	−0.93	−0.96	5.85	0.09
	(0.75)	(2.39)	(−4.52)	(−0.54)	(2.44)	
1-Year	−0.05	0.93	−1.31	3.89	7.76	0.11
	(−0.31)	(2.86)	(−4.08)	(1.17)	(1.70)	

Two key variables, nearness to its historical high (x_{max}) and nearness to its 52-week high (x_{52}), are introduced as predictors of future market returns. First, the paper tests for monthly overlapping regression of future returns on past returns. Previous research has pointed out strong momentum effects in the cross-section analysis but this paper focuses on time-series analysis. The past excess returns do not predict future returns when they are regressed alone (only marginally significant at a 1-month horizon). However, when x_{max} is added, the past return is a significant indicator for positive future returns. In addition, the negative significant x_{max} strengthens the paper's hypothesis. When x_{52} is added, the statistical power of past returns is decreased significantly, confirming that they capture important information about market expectations that traditional past-return measures do not. The x_{52} positively predicts future returns and x_{max} negatively predict future returns, with the power of x_{52} greater than x_{max}. A 1% increase in x_{max} is associated with a more than 1% decrease in expected returns over the next year, making it an important risk factor for investors. These relationships hold up to a one-year horizon, demonstrating both statistical and economic significance of the short-term predictability of the two indicators. Traditional predictors of market returns, such as dividend yield, interest rates, and macroeconomic indicators, tend to perform better at longer horizons (more than one year), so these indicators can be useful complements. In addition, one advantage is that the two indicators are based on data up to the current time, not predictive indicators such as consumption-growth rate.

Because the correlation between x_{52} and x_{max} is very high (86%), the regression can be affected by multicollinearity. However, the paper does not have low t-statistics normally caused by multicollinearity. In addition, the variance inflation factor is 3.4, below the standard cutoff of 10.0, indicating that both variables provide independent information about expected returns.

3.2 NYSE/ AMEX

Table 3
Monthly overlapping regression with macro control.

In this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted excess returns onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal-historical high indicator I_t, default premium def_t, term premium $term_t$, real interest rate r_t^f, inflation rate π_t, consumption–wealth ratio cay_t, dividend yield dp_t, and surplus ratio s_t. We use overlapped monthly sampled data, except for cay_t and s_t, which are only available at quarterly frequency. The Newey–West t-stat given in parentheses control for heteroskedasticity and autocorrelation. The coefficients for D_t, I_t, and def_t are in terms of percentage. Our sample data are monthly from 1958.01 to 2009.12.

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	s_t	R^2
1-Month	0.08	0.12	−0.15	−0.66	0.54	−0.39	0.26	−0.80	0.15	0.20	0.44	0.04	0.05
	(1.52)	(2.21)	(−3.54)	(−0.99)	(1.14)	(−0.48)	(1.06)	(−0.44)	(0.09)	(1.50)	(1.98)	(0.44)	
3-Month	0.07	0.37	−0.47	−1.93	2.01	−0.19	0.07	−5.39	−3.7	0.86	1.14	0.00	0.13
	(0.76)	(2.36)	(−3.69)	(−1.54)	(1.48)	(−0.10)	(0.12)	(−1.05)	(−0.82)	(2.49)	(1.80)	(−0.01)	
6-Month	0.02	0.68	−0.87	−2.23	3.24	0.65	−0.30	−11.52	−6.66	1.86	1.84	−0.11	0.21
	(0.18)	(2.84)	(−4.06)	(−1.44)	(1.19)	(0.24)	(−0.32)	(−1.59)	(−0.93)	(2.53)	(1.50)	(−0.23)	
1-Year	0.00	0.74	−1.23	2.83	1.39	−5.20	0.47	−11.91	−0.65	3.44	2.81	−0.59	0.32
	(0.03)	(2.33)	(−4.00)	(1.12)	(0.28)	(−1.00)	(0.29)	(−0.96)	(−0.05)	(2.59)	(1.13)	(−0.73)	

Many previous studies have pointed out that variables related to the business cycle, such as the default spread, term spread, interest rate, inflation rate, dividend yield, consumption–wealth ratio, and surplus ratio, can predict future market returns. The two predictors are, in fact, correlated to these variables, but they still have predictive power on their own. If the two main predictors simply capture the same information as these traditional variables, their significance would be questionable. To test this, the author uses monthly overlapping regression. Again, the t-statistics for x_{max} is significantly negative and x_{52} is significantly positive, with a higher magnitude than traditional variables such as cay and dividend yield in the period of less than one year. This confirms that the findings are not merely driven by business cycle fluctuations.

Another concern is that n_max could simply be capturing a mean-reverting component of stock returns rather than behavioral effects. To test for robustness of the regression, instead of the Dow index, the authors regress excess returns on the NYSE/Amex total market value index. If the findings were because of mean-reverting, the predictors derived from the NYSE/Amex market cap should exhibit similar predictive power. The regression shows that x_{52}^{NY} is no longer significant and x_{max}^{NY}, even though statistically significant, its magnitude is much smaller than of the Dow index. This indicates that the availability and recognition of the Dow index can help predict future excess returns of the market. With the regression of both Dow and NYSE/Amex, the predictability of x_{52}^{NY} and x_{max}^{NY} is no longer significant. The findings strongly support the anchoring and limited investor attention hypotheses of this paper. The Dow index is a highly visible market benchmark that receives high recognition, making it a very well-known anchoring point for investors.

3.3 Subsample analysis

To further strengthen the test of the predictability, the authors divided the sample into three periods. For the two main psychology variables, they are statistically significant throughout the three periods with a slightly different magnitude. In addition, the results indicate that most business cycle variables exhibit inconsistent predictive power across subsamples. For example, st has no predictive power in the first two subsamples for horizons of one year or less and the dp_t, which is only marginally significant in the whole sample, shows strong predictive power in all three subsamples. Besides, the term premium is mainly predictive only in the early subsample, and the default premium exhibits changing signs across the three subsamples. With this subsample regression, we can see that traditional macroeconomics does not predict consistently across time period, and the two main predictive variables of the paper succeed in doing so.

3.4 Small sample bias and out-of-sample R^2

To test for the small sample bias, the authors use the Monte Carlo simulation to see if the significant t-test is affected by the size of the data. Under the null hypothesis that the excess returns are unpredictable, the x_{52} and x_{max} are regressed in vector autoregression. As a result, the paper finds that the smaller the period, the smaller the size bias. Furthermore, because of the size bias for the longer period, they find that the t-statistic needs to be higher to confirm the results are statistically significant. This small sample bias test, however, does not change the fact that both x_{52} and x_{max} have predictive ability for future returns because the t-statistics are high for these variables. In addition, the Monte Carlo test also confirms that the above regressions are not affected by multicollinearity.

To test for the out-of-sample analysis, the paper tests for out-of-sample R^2 by comparing mean squared forecast errors against a historical mean forecast. The positive R^2 means that both x_{52} and x_{max} can predict out-of-sample, even though the magnitude is small.

3.5 Monte Carlo

To further strengthen their analysis, the authors use extensive Monte Carlo simulations to test and rule out any alternative explanations of the return predictability. Because of the nature of the Dow index whose prices tend to increase over time, both the predictors of the paper are highly skewed. This is a potential concern as the skewness can affect the statistical significance of the results. The Monte Carlo simulation is used to test the true ability of the predictors. According to the author, if the reordering of the Dow index diminishes the predictability, the two predictors of the paper should be significant. In other words, the x_{max} will have no statistical inference for the future returns after reordering. The result is that the highly statistically significant coefficient of the return-randomization experiment indicates that both x_{52} and x_{max} have predictive behavior and not because of the time series regularities of the Dow Jones.

To further test the true predictive power of the variables, the authors resample returns with replacement to replicate a bootstrap approach. The result is that the t-statistics are still consistent, further confirming the key points of the paper. In addition to that, since the returns of Mondays differ from other days, the author separately randomizes Monday and non-Monday returns to test whether the weekend effect influences the results. Again, the significance levels are still consistent, confirming that the weekend effect does not impact the findings.

The VAR(1) and VAR-GARCH(1,1) regression also confirms the fact that observed predictability is not simply a result of standard time-series or the volatility clustering effects. The simulation for total market returns instead of excess returns and returns directly of the Dow index also further strengthens the paper's main findings. In conclusion, the psychology anchoring and limited attention effects are robust to multiple statistical tests, and the return predictability remains statistically significant across different randomization, bootstrap, and modeling approaches.

3.6 International data

This study analyzes outside the United States and into six other G7 countries — the United Kingdom, Germany, France, Japan, Canada, and Italy — with stock indexes such as the FTSE 100, DAX, CAC 40, NIKKEI, SPTSX, and FTSEMIB. Similar to the US's Dow index, these stock indexes are well-recognized and can act as an anchoring effect for investors. The study shows that by calculating x_{52} and x_{max} for each country and using them in predictive regressions, these proxies maintain their predictive power for future market returns. Many coefficients, despite the shorter sample period, remain statistically significant. x_{52} and x_{max} have a strong forecast of returns in the U.K. and Italy, while individual significance appears in Germany (x_{max} at the one-year horizon), France, and Canada (x_{52} at the one-year horizon). In addition to that, all the coefficients have the right sign, indicating the predictive power of the two variables. Furthermore, evidence is provided in the foreign exchange market, where Wang, Yu, and Yuan (2010) show nearness to exchange rate highs predicts currency movements. This serves as out-of-sample validation, increasing the confidence concerning the robustness of the anchoring effects across financial markets around the world.

3.7 Cross-sectional data

In this section, the authors extend the analysis to the cross-section of expected stock returns, particularly in relation to momentum and value investing strategies. The goal is to understand how psychological anchoring influences stock returns across different groups of stocks and investment strategies.

In the above time-series regression, if a stock's x_{52} equals x_{max} of that period, then nearness to the 52-week high serves as a stronger anchoring effect for investor underreaction. In contrast, if a stock has different 52-week and historical highs, it suggests that overreaction may be captured by the book-to-market ratio, aligning with value investing principles. To test these ideas, stocks are divided into two groups based on whether x_{52} is equal to x_{max} or whether they are different, following the momentum trading framework of George and Hwang (2004) and Jegadeesh and Titman (1993). In a standard momentum strategy, stocks are then ranked based on past six-month returns. The strategy goes long on winners and short on losers, holding the portfolio for six months. The results show that momentum effects are significantly stronger when a stock's 52-week high equals its historical high, specifically three times more than when x_{52} does not equal x_{max}. Furthermore, a variation of the momentum strategy is implemented by selecting only stocks where the historical high is larger than the 52-week high. Here, momentum effects weaken, confirming that the historical high influences price dynamics in a way that contradicts traditional momentum patterns.

Beyond momentum, the study examines whether x_{max} impacts the value investment strategy, where stocks are ranked based on book-to-market ratios. With a high alpha for the strategy, the results indicate that the returns from value investing are much larger when the 52-week high is below the historical high, supporting the idea that overreaction plays a stronger role for these stocks. The effect holds for both value-weighted and equal-weighted returns, emphasizing its robustness. As a result, the momentum strategy works better when x_{52} equals x_{max}, and the value strategy works better when $x_{52} < x_{max}$.

In addition, the paper uses a double-sorting strategy. Stocks are first ranked by nearness to the historical high and then further subdivided into quintiles based on nearness to the 52-week high. The results point out that the returns from this double-sorting strategy are much larger than the above sorting strategy. In addition to that, the result also points out that nearness to the historical high weakens momentum effects, reinforcing the hypothesis that investors overreact to long-term price trends. Applied to value investing, when sorting stocks based on nearness to the historical high first, a one-way sort based on nearness to the historical high created insignificant negative results. In contrast, after controlling for nearness to the 52-week high, the return spread significantly increases by about 1.23% per month.

In conclusion, the cross-sectional analysis confirms the predictive power of the two suggested variables. In particular, the results point out that x_{52} and x_{max} have different power in predicting future returns of different investment strategies.

4. Critical assessment

The author presents very good evidence that nearness to the 52-week high and nearness to the historical high predict future aggregate market returns, offering a financial behavior that is caused by investor anchoring and limited attention. Besides, the research succeeds in bringing individual stock predictions to broader market predictions. In the paper, the authors use extensive time-series regressions, cross-sectional analysis, Monte Carlo simulations, and international data to strengthen their main findings. In addition to that, all the findings are statistically significant and very robust, with the t-statistics better than traditional macroeconomics variables. Furthermore, the findings are not subject to small-sample bias, multicollinearity, mean-reverting, or volatility clustering.

However, some alternative explanations, possible biases, and some supplementary robustness tests could further strengthen the conclusions. First, while the present study includes macroeconomic predictors like default spreads and term spreads, business cycle phases (expansions or recessions) could still affect the results. For example, during an expansion, the tendency of markets is to reach new highs, which can lead to potential endogeneity between x_{max} and broader economic conditions. This could lead to possible biased estimates and affect the causal relationship of the two main predictors. A robustness check could involve controlling for expansion and recession indicators. The recession data from the National Bureau of Economic Research can be used as a control for the regression. Second, because of the fact that behavioral biases might not be fully captured in linear regressions, nonlinear models (decision trees or neural networks) could test whether these variables exhibit nonlinear relationships with future returns.

Overall, the article provides strong evidence that nearness to the 52-week high and historical high predicts future market returns, and the authors present a convincing behavioral explanation based on investor underreaction and overreaction with extensive robustness and sample tests.

II. Analysis Replication

To check the article's main results' reliability, we replicate the paper analysis empirically by using the same applied methods and databases, with a couple of additional twists to enhance the compatibility of the research within the contemporary context. Overall, we rerun the first 6 tables of the paper, using the data from CSRP, Fama French Library, DowJones, Lettau and Ludvigson's website, and FRED from 1953 to 2019. The small 'twist' we include in the replication is that we cover a longer period for the regression (1953-2019 instead of 1958-2009 as in the original paper)

Table 1 - Replicate

Panel A: Summary statistics

	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	S_t
Mean	0.6	0.94	0.9	0.05	0.54	0.97	1.14	0.28	0.06	-0.2	0.68	0.52
Std	4.24	0.07	0.1	0.23	0.5	0.45	1.33	0.36	0.33	1.9	1.44	0.19
AC(1)	0.06	0.89	0.94	0.13	0.94	0.97	0.55	0.56	0.46	0.97	0.99	0.99
Skewness	-0.4	-1.84	-1.24	3.92	-0.14	1.8	0.15	0.11	1	-0.27	-0.24	0.35
Kurtosis	0.97	4.22	1.44	13.4	-2	4.3	-0.15	2.6	1.3	-0.52	-1.5	-0.66

Panel B: Correlation matrix

	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	S_t
r_t	1.00											
x_{52}	0.38	1.00										
x_{max}	0.25	0.83	1.00									
D_t	0.14	0.22	0.25	1.00								
I_t	0.03	0.28	0.59	0.22	1.00							
def_t	0.02	-0.35	-0.45	-0.13	-0.36	1.00						
$term_t$	0.12	0.05	-0.1	0.03	-0.06	0.2	1.00					
π_t	-0.1	-0.15	-0.24	-0.12	-0.27	0.09	-0.31	1.00				
r_t^f	0.03	0.06	0.18	0.06	0.19	0.14	-0.14	-0.73	1.00			
cay_t	0.05	0.08	0.17	0.1	0.29	-0.11	0.18	-0.2	0.24	1.00		
dp_t	-0.03	-0.11	-0.03	0.05	-0.07	-0.07	-0.57	0.21	0.13	0.02	1.00	
S_t	-0.07	-0.14	-0.16	-0.08	-0.26	0.25	-0.5	0.5	0.11	-0.1	0.59	1.00

Table 1 summarizes statistics, including mean, standard deviation, autocorrelation, skewness, and kurtosis, of the two main predictors and other macroeconomic factors. Because of the stock-growing tendency of the Dow Jones index, the means of both x_{52} and x_{max} are close to one, highly correlated to each other (83%), but not highly correlated with other macroeconomic variables, which is similar to the original paper results. The highest correlation with macroeconomics variables is between x_{max} and It, at a correlation of 0.59. Even though the correlation between the two main predictors is high, including both of them in the regression would be necessary as they predict opposite tendencies of the future market aggregate returns. In addition, x_{52} and x_{max} are both skewed as they are bounded by 1 from above, but the Monte Carlo simulation will confirm their robustness when running regressions. When considering the correlation with current return, x_{52} shows a positive sign of 0.38, indicating that when the Dow index is closer to its 52-week high, it tends to show a positive return. This aligns with the main finding that proximity to the 52-week high could indicate momentum or overreaction, where market participants are too optimistic when the index is near its high. While the Dow index when near its historical high shows a tendency for positive returns, the effect is weaker than that of the 52-week high, only at 0.25, suggesting investors' underreaction towards excess returns, good news. Additionally, the weak correlation between D_t and the excess return of 0.14 further suggests that the historical high indicator doesn't have a strong predictive power for returns. Finally, the trivial correlation of I_t and excess return, 0.03, implies that, when the 52-week high is also historically high, it does not have meaningful predictive effects on returns. The reason behind this could be that the market conditions are more stable or neutral, with no remarkable overreaction or underreaction in this situation.

Table 2 - Replicate

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	R^2
1-Month	0.06 (1.36)					0.004
3-Month	0.05 (1.14)					0.003
6-Month	-0.06 (-1.3)					0.003
1-Year	0.05 (1.3)					0.003
1-Month	0.08 (1.8)		-3.9 (-1.79)			0.01
3-Month	0.07 (1.55)		-3.31 (-1.49)			0.007
6-Month	-0.04 (-0.82)		-4.03 (-2.3)			0.01
1-Year	0.07 (1.67)		-3.5 (-1.94)			0.01
1-Month	0.07 (1.56)	8.95 (1.65)	-13.1 (-3.28)	-0.09 (-0.17)	1.136 (2.58)	0.02
3-Month	0.06 (1.36)	6.87 (1.2)	-10.28 (-2.3)	-0.2 (-0.35)	0.87 (1.75)	0.01
6-Month	-0.03 (-0.75)	-0.49 (-0.1)	-5 (-1.15)	0.66 (0.88)	0.26 (0.56)	0.01
1-Year	0.07 (1.55)	-1.99 (-0.42)	-2.47 (-0.59)	0.96 (1.85)	-0.11 (-0.22)	0.01

Table 2 summarizes our future returns regression on past market returns (r_t), nearness to the 52-week high (x_{52}), nearness to the historical high (x_{max}), the Dow historical high indicator (D_t), and the Dow 52-week high equal-historical high indicator (I_t) on future market returns. The regression is conducted at four horizons: 1-month, 3-month, 6-month, and 1-year, using overlapping monthly data.. In the first part of the table, we regress excess market returns on only their lagged variables at different horizons. With no significant t-statistics at the 5% level, above -1.96 and below 1.96, the past returns have no predictive power over future returns, hence no strong momentum effect for all time horizons. When nearness to historical high x_{max} is added, the t-statistics of the past returns increase but still only marginally significant for all time horizons, and remain weak predictors. On the other hand, the x_{max} coefficient, indicating it can negatively predict future market returns, is more statistically significant. Notably, at a 6-month horizon, this coefficient is statistically significant atthe 5% level, implying 4 points lower in return for a point increase in x_{max}. When x_{52}, D_t, and I_t are added, the statistical power of past returns decreased, but that of x_{max} is significantly higher at horizons of 1-month and 3-month. When the past 52-week high equals its historical high, the variable significantly predicts positive future returns at a 1-month horizon, at 1.136 level. This indicates that the power of the 52-week high in anchoring is stronger than that of the historical high, and investors will underreact to the recent good news.

Table 3

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	S_t	R^2
1-Month	0.05	10.34	-13.40	-0.36	0.87	0.33	0.11	-0.68	-0.25	0.15	0.33	-1.95	0.035
	(1.06)	(1.80)	(-3.14)	(-0.64)	(1.84)	(0.38)	(0.43)	(-0.32)	(-0.13)	(1.25)	(2.17)	(-1.05)	
3-Month	0.04	9.42	-10.98	-0.43	0.64	0.77	-0.06	-1.43	-0.94	0.16	0.30	-1.85	0.038
	(0.69)	(1.57)	(-2.27)	(-0.74)	(1.21)	(1.14)	(-0.26)	(-0.69)	(-0.48)	(1.41)	(1.93)	(-0.89)	
6-Month	-0.05	1.40	-5.93	0.46	-0.18	0.37	-0.06	-0.74	-0.25	0.24	0.23	-2.53	0.038
	(-1.16)	(0.24)	(-1.24)	(0.61)	(-0.36)	(0.71)	(-0.28)	(-0.46)	(-0.15)	(2.11)	(1.46)	(-1.28)	
1-Year	0.06	-2.74	-2.36	0.82	-0.55	-0.50	0.30	1.54	2.14	0.09	0.22	-3.12	0.03
	(1.40)	(-0.52)	(-0.54)	(1.58)	(-1.11)	(-1.02)	(1.36)	(0.95)	(1.29)	(0.83)	(1.22)	(-1.58)	

To confirm that the predictive powers of the two main variables are not due to their correlation with other macroeconomic variables, we run monthly overlapping regression of past returns on the two main psychology variables and other macro variables. The t-statistic for x_{max} is significant at both 1-month and 3-month horizons, and for x_{52} at the 1-month horizon. The coefficients of x_{max} are always negative, indicating the negative future returns. The coefficients of x_{52}, however, change from positive to negative at a 1-year horizon, even though it is statistically insignificant. The macroeconomics variable dp_t is also significant, although its t-statistics are not as high as those of x_{max}.

Table 4

Panel A: NYSE/Amex market cap as benchmark

Horizon	r_t	x_{52}^{NY}	x_{max}^{NY}	D_t^{NY}	I_t^{NY}	R^2
1-Month	0.6	3.88	-5.6	0.14	0.45	0.01
	(1.27)	(0.7)	(-1.58)	(0.34)	(0.79)	
3-Month	0.05	1.19	-4.2	0.52	0.16	0.01
	(0.98)	(0.23)	(-1.08)	(1.18)	(0.24)	
6-Month	4.58	-5.78	2.26	0.72	-1.06	0.02
	(1.79)	(-1.32)	(0.62)	(1.63)	(-1.84)	
1-Year	1.70	-1.41	0.78	-0.39	-0.63	0.01
	(0.67)	(-0.35)	(0.24)	(-0.92)	(-1.12)	

Panel B: Horse race between the Dow index and NYSE/Amex market cap

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	x_{52}^{NY}	x_{max}^{NY}	R^2
1-Month	3.90	5.83	-17.42	-0.01	1.02	2.36	4.90	0.03
	(1.06)	(0.74)	(-3.05)	(-0.02)	(2.36)	(0.31)	(1.28)	
3-Month	3.73	8.44	-13.70	-0.22	0.76	-2.65	4.12	0.01
	(1.05)	(1.00)	(-2.25)	(-0.38)	(1.56	(-0.36)	(1.02)	
6-Month	5.78	-1.12	-8.17	0.69	0.15	0.09	3.73	0.02
	(2.24)	(-0.13)	(-1.40)	(0.91)	(0.32)	(0.01)	(0.97)	
1-Year	4.12	-9.40	-2.06	1.04	-0.25	8.04	-0.16	0.02
	(1.62)	(-1.24)	(-0.36)	(1.98)	(-0.54)	(1.26)	(-0.04)	

To check whether x_{max}'s predictive power is because of the mean-reverting state, we replace x_{52} and x_{max} of the Dow index with nearness to the 52-week high and nearness to a historical high of the NYSE/Amex total market value x_{52}^{NY} and x_{max}^{NY}. Panel A shows that both x_{52}^{NY} and x_{max}^{NY} do not have predictive power. The same results are indicated after we run a horse race regression between the Dow index and the NYSE/ Amex. The x_{max} is still a statistically significant inference for the negative future returns.

Table 5

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	S_t	R^2
Panel A: Subsample: 1953.05 - 1974.12													
1-Month	0.01	27.05	-32.51	-0.68	0.76	0.83	1.30	2.98	4.28	0.30	0.55	-5.13	0.14
	(0.08)	(3.00)	(-2.92)	(-0.97)	(1.13)	(0.56)	(1.56)	(0.37)	(0.54)	(1.01)	(0.81)	(-1.01)	
3-Month	0.06	12.03	-28.07	0.41	0.69	1.05	-0.03	-12.84	-10.36	-0.04	0.47	4.32	0.15
	(0.62)	(1.35)	(-2.97)	(0.57)	(1.17)	(0.77)	(-0.06)	(-2.50)	(-1.91)	(-0.13)	(0.78)	(1.19)	
6-Month	-0.04	-0.05	-15.83	0.98	-0.61	-0.69	0.95	-0.19	1.39	0.54	0.11	0.85	0.12
	(-0.60)	(-0.00)	(-1.30)	(1.35)	(-0.95)	(-0.39)	(1.56)	(-0.05)	(0.31)	(1.83)	(0.16)	(0.26)	
1-Year	0.06	4.76	-13.97	0.82	-1.19	-1.88	0.08	-3.63	-3.02	0.17	0.18	0.55	0.05
	(0.87)	(0.34)	(-0.92)	(1.03)	(-1.49)	(-0.82)	(0.10)	(-0.56)	(-0.48)	(0.51)	(0.22)	(0.16)	
Panel B: Subsample: 1975.01 - 2003.09													
1-Month	0.02	7.36	-21.83	0.39	1.96	1.93	-0.53	-5.28	-3.86	0.73	2.61	-8.56	0.11
	(0.40)	(0.86)	(-3.05)	(0.31)	(1.62)	(1.68)	(-1.24)	(-1.80)	(-1.28)	(2.27)	(2.48)	(-1.52)	
3-Month	0.00	13.83	-17.48	-1.76	1.23	-0.16	0.30	2.55	2.19	0.07	2.55	-14.92	0.06
	(0.06)	(1.59)	(-2.21)	(-1.23)	(1.10)	(-0.18)	(0.75)	(0.90)	(0.76)	(0.22)	(2.93)	(-2.68)	
6-Month	0.01	7.50	-10.57	-2.16	0.50	-0.18	0.22	2.51	1.59	0.10	2.65	-16.26	0.06
	(0.18)	(0.95)	(-1.50)	(-0.97)	(0.42)	(-0.19)	(0.60)	(0.99)	(0.63)	(0.31)	(2.55)	(-2.70)	
1-Year	0.07	1.30	-11.46	0.76	-0.21	-2.48	0.61	4.75	6.85	-0.18	2.48	-14.21	0.08
	(1.03)	(0.16)	(-1.60)	(0.74)	(-0.20)	(-3.16)	(1.73)	(1.92)	(2.76)	(-0.79)	(2.42)	(-2.40)	
Panel C: Subsample: 2003.10 - 2019.09													
1-Month	0.15	-17.55	-8.02	0.55	-0.84	-5.14	-1.47	-8.51	-8.77	0.15	1.37	-8.23	0.1
	(1.56)	(-1.18)	(-0.86)	(0.54)	(-0.72)	(-2.50)	(-2.80)	(-1.53)	(-1.51)	(0.30)	(0.49)	(-0.97)	
3-Month	0.06	-2.57	-3.32	-0.09	-1.13	-0.33	-1.12	-6.09	-6.34	0.27	-1.63	-4.07	0.05
	(0.68)	(-0.24)	(-0.30)	(-0.08)	(-0.93)	(-0.19)	(-1.69)	(-1.03)	(-0.99)	(0.56)	(-0.57)	(-0.55)	
6-Month	-0.21	-12.13	-0.72	2.35	-2.28	-0.19	-1.27	-7.32	-7.05	0.86	-6.99	0.98	0.18
	(-2.91)	(-1.15)	(-0.09)	(3.11)	(-1.87)	(-0.13)	(-2.01)	(-1.29)	(-1.29)	(1.89)	(-2.88)	(0.16)	
1-Year	0.01	9.64	-6.37	1.22	-0.82	2.36	0.09	-6.26	-6.73	-0.04	-3.26	13.12	0.06
	(0.14)	(0.79)	(-0.71)	(1.36)	(-0.57)	(1.55)	(0.15)	(-0.90)	(-1.00)	(-0.11)	(-0.89)	(2.17)	

To further test the predictive power of the proposed variables, we divide the sample into three subsample periods: 05/1953 - 12/1974, 01/1975 - 09/2003, and 10/2003 - 09/2019. Our dataset extends a decade beyond the original study, which used data up to 2009. We decided to limit our sample to September 2019 to avoid abnormal market trends caused by the COVID-19 pandemic. This allows us to assess the robustness of our findings in a more stable economic environment. For the x_{max}, the t-statistics are significant at the 1-month and 3-month horizons for the first two subsamples, but are insignificant for the third subsample. The predictive power of x_{52} is only significant at the 1-month horizon of the first subsample.

Table 6 - Small sample bias and out-of-sample analysis

Panel A: Small sample bias				
	1-Month	3-Month	6-Month	1-Year
Size(52-week)	2.42%	2.47%	2.41%	2.65%
Size(max)	2.57%	2.49%	2.46%	2.72%
Size(52-week + max)	0.34%	4.61%	5.16%	3.56%
t(52-week)	1.96	1.93	1.97	1.98
t(max)	-1.98	-1.91	-1.99	-1.96
$\bar{R}^2$	0.00, 0.0246	0.00, 0.0245	0.00, 0.0248	0.00, 0.0264

Panel B: Out-of-sample R^2

Predictive variables	1-Month	3-Month	6-Month	1-Year
x_{max}	0.038	0.088	0.091	0.081
$x_{52} + x_{max}$	0.121	0.217	0.207	0.147

In this table, the Monte Carlo experiments' small sample results are presented. We count all the times whenever the t-statistic's absolute value of nearness to the 52-week high exceeds 1.96 and calculate its proportion over all periods. Size(max) is the percentage of times the t-statistic's absolute value for x_{max} is greater than 1.96; Size(52-week + max) is the percentage of times both x_{52} and x_{max} have t-statistic absolute values that are above 1.96. The 97.5% quantile of the t-statistics for x_{52} in Monte Carlo trials is t(52-week). In Monte Carlo simulations, t(max) is the 2.5% quantile of x_{max}'s t-statistics. R-squared bar is the Monte Carlo-yield R^2's 95% confidence interval. Out-of-sample forecast results are reported in Panel B. The data up to month t is used to estimate the coefficients. For every month t, different future cumulative excess returns, 1-month, 3-month, 6-month, and 1-year, are regressed on past nearness to x_{52} and x_{max}. We start with the first 20 years of data, add one month at a time, and then conduct recursive estimation. Two methods are used to run the out-of-sample analysis: one uses only nearness to the historical high as a predictor, while the other uses both nearness to the historical high and nearness to the 52-week high as forecasters. We compare both strategies to the best strategy using the historical mean as forecast for the next period's semiotic premium, and we report the out-of-sample R^2 by comparing the mean-squared-error of the mentioned strategies with the historical mean predictors.

For panel A of the report, we can see that the size percentages for x_{52} and x_{max} is not very high across all forecast horizons, ranging from 2.42% to 2.65% for Size(52-week) and slightly higher for Size(max) (2.57% to 2.72%). In addition, when x_{52} and x_{max} are combined, the size is much higher for horizon longer than 3-month (4.61%), for example 6-month (5.16%) horizons, before declining over 1-year (3.56%), indicating that there is an increased risk of over rejecting the null hypothesis when using multiple predictors. The t-statistics for all the variables are statistically significant, except for the 3-month horizon. However, with the low R^2, the actual explanatory power for returns is quite low. For panel B of the report, out-of-sample R^2, we can see that the predictive power of our variables is strongest at 3-month and 6-month horizons, reaching R2= 0.217 at 3 months and 0.207 at 6 months, before declining to 0.147 at 1 year. Furthermore, the model performs much better when both variables are included. These results suggest that while stocks near their 52-week or historical highs present some return predictability, the effect weakens over longer horizons after 3 months. To sum up, regardless of some statistically significant effects, the explanatory power is low, implying that the stock returns are likely to be driven by other factors.

Conclusion

To conclude, the replication analysis strengthens the original paper findings, at the same time, reveals certain variations. Aligned with the original results, the nearness to 52-week high x_{52} and nearness to historical high x_{max} imply significant predictive power for future market returns. Except for that, the trend seems to be reversed as the forecasting effects in the original paper increase at longer time horizons, while our analysis shows the higher trends at shorter time horizons. Our results show that over longer time periods, these factors' predictive power decreases, and statistical significance disappears after six months. The change in results, where the long-term predictive power of psychological anchors decreases, is likely due to our sample including 10 years of more recent data than the original study. This captures shifts in investor behavior after the global financial crisis, where market participants may have become more risk-averse and responsive to short-term trends. Consistent with the original study's finding that investors could overreact to recent favorable news, the data show that the Dow Jones index tends to provide positive returns when it is closer to its 52-week high. Further evidence that market participants underreact to historical highs comes from the analysis of the historical high indicator (D_t) and the combined effect of the 52-week high matching the historical high (It). Both indicators have poor predictive ability. Monte Carlo simulations and out-of-sample analysis similarly support the findings' robustness, but they also show how little these psychological anchor variables can explain in terms of stock return prediction. According to the subsample study, the predictive value of x_{max} and x_{52} is weaker in the most recent sample than it was in previous periods, indicating potential shifts in market dynamics over time. Overall, the study confirms the main idea of the original paper, which was that psychological anchors affect market returns. However, the findings show that the significance of these effects varies depending on the time horizon and market conditions, and that other macroeconomic factors probably have a greater impact on stock returns.

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