Do investors care about negative returns?[1]

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Abstract

In this paper, we analyse the impact of frequent negative returns and the recency bias on future stock market returns. Specifically, we propose a strategy that is based on counting of daily negative returns during the previous month, where investors earn 11.9% p.a. Our results show that weighting returns exponentially outperforms equal-weighting and is robust to a range of existing risk factors and the firms' characteristics, suggesting that the most recent observations during the month receive more investors' attention and are the most relevant for future performance. The exponentially weighted strategy remains significant for stocks in the S&P 500 after transaction costs. Although the return of the exponentially weighted strategy is positive for stocks held by institutional and retail investors, it is the highest for stocks that are largely held by retail traders.

JEL Codes: G11, G12, G40

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1 Introduction

The standard assumption in asset pricing is that agents possess rational expectations (RE) about the economy. The RE assumption states that agents know the structural model of the economy and the objective probability distribution in equilibrium. In order to generate time-varying equity premium under RE, different modifications of the agent's utility function (e.g. Campbell and Cochrane (1999), Barberis and Huang (2001)) or modifications of the endowment process (Bansal and Yaron (2004)) have been proposed. However, the recent literature (Greenwood and Shleifer (2014), Barberis et al. (2018), Da et al. (2021)) argues that agents depart from RE and form their beliefs about future returns using extrapolation. In this paper, we investigate if the *frequency of past negative returns* shapes expectations about stock future performance. We present empirical evidence that the frequency of negative daily returns in the previous month predicts future monthly returns in the cross-section of stocks. Moreover, we show that particularly recent losses have a significant impact on the forecasting of future returns.

The idea that people perceive gains and losses differently and exhibit loss aversion has been extensively studied since Kahneman and Tversky (1979). Proposing a descriptive model of decision-making under risk, called prospect theory, Kahneman and Tversky (1979) argue that people perceive outcomes as gains and losses defined with respect to some reference point, whereby losses loom larger than gains. Additionally, to the analysis of differences in preferences over gains and losses, Kuhnen (2015) examines how gains and losses affect belief formation. She shows that people demonstrate asymmetric learning from gains and losses when forming subjective posterior beliefs and may react too pessimistically when observing negative payoffs. Her results demonstrate that the difference in posterior beliefs is not caused by risk preferences. Kuhnen (2015) furthermore documents that investment decisions are driven by subjective beliefs and not by the risk preferences over positive or negative domains. Da et al. (2021) present evidence that past returns shape the beliefs of the investors and are related to future returns in the cross-section of stock returns. Moreover, Cosemans and Frehen (2021) argue that investors use past return distribution as a proxy for the formation of expectations about future performance. By paying more attention to past salient returns, investors extrapolate past returns when making investment choices.

In contrast to Cosemans and Frehen (2021) who analyse the distortion of beliefs by the magnitude of the large positive and negative returns, we investigate the role of negative and positive returns without considering their magnitude. In order to study belief formation, we count the number of upward and downward movements in daily returns over the past month. Motivated by the findings of Barberis and Huang (2001) and De Long et al. (1990) that investors are reluctant to hold stocks that show a high frequency of negative returns, we argue that investors use simple heuristics and count the number of daily returns below zero when forming expectations about next-month returns. Tversky and Kahneman (1974) show that people operate with simple heuristics or 'rules of thumb' when making decisions. Instead of spending time gathering, analysing and updating information to make a rational decision, people use simple rules to minimize processing time necessary for decision-making. An example of such a simple heuristic is binary thinking, which is widely discussed in psychology (Fisher et al. (2018), Oskarsson et al. (2009), Isaac and Schindler (2014)). Binary thinking represents the tendency of people to split data into two mutually exclusive groups. According to Fisher and Keil (2018), people possess a binary bias, which means that agents compress continuous data into discrete categories, leading to distortion in the data aggregation that affects expectations. Given the binary bias, we assume that investors represent the stock return as a binary lottery with only two possible outcomes: positive or negative return. We further discuss how binary representation of the return distribution impacts the expectation formation process of the agent.

We build on the vast literature that analyses the hot-hand fallacy (Gilovich et al. (1985)), which states that after observing a sequence of negative binary outcomes the agent beliefs that future outcomes will be also negative.[1] Given that the agent does not know the future stock return

[1] This belief pattern contradicts the gambler's fallacy (see e.g. Rabin (2002)), which argues based on the law of small numbers that for an i.i.d process with the probability of the positive outcome equal to the probability of the negative outcome the agent expects a positive outcome after a series of negative outcomes because the series must be representative of the population. However, Edwards (1961) and Rabin and Vayanos (2010) claim that when the objective distribution is unknown, the agent is more inclined to the hot-hand-fallacy.

distribution, we assume that investors are prone to the hot-hand fallacy (see e.g. Edwards (1961), Rabin and Vayanos (2010)). Namely, after observing a series of negative returns, the agent believes that the sequence of negative returns will persist without taking into account the fundamental characteristics of the firm. To construct the empirical measure that can capture the effect of the hot-hand fallacy in the stock market, we count the number of daily negative returns per month. Evidence that counting heuristics help to make inference about the stock market has been recently studied in the literature (Ungeheuer and Weber (2021), Chesney et al. (2019)). We concentrate on counting the negative returns based on Holzmeister et al. (2020) and Huber et al. (2019) who experimentally show that frequency of negative returns is the most salient characteristic of the return distribution for investors.

Assuming that investors count the number of positive and negative returns, we analyse the case where the investor counts the number of daily negative returns in the previous month and bases her investment decision on the fraction of returns below zero, which we call frequency of loss (FL). Given the evidence of recency bias (Malmendier and Nagel (2011), Malmendier and Nagel (2016), Nagel and Xu (2022)) and the hot-hand fallacy (see e.g. Gilovich et al. (1985)) that the most recent observations play a larger role than the more distant ones in shaping beliefs, we further construct a measure that we call the weighted frequency of loss (WFL). This measure is based on the weighted frequency of the negative daily returns in the previous month, where the weights follow an exponential function, with more weight put on more recent observations (Da et al. (2021)).

Since investors suffer from a narrow framing bias when making risky decisions (Razen et al. (2020)), we furthermore assume that they consider each stock individually when constructing FL and WFL measures. Given that investors with higher sensitivity to past price trends exhibit greater under-diversification (Goetzmann and Kumar (2008)) and that investors who adopt narrow framing when making investment decisions hold a less-diversified portfolio (Kumar and Lim (2008)), the risk for holding stocks that have frequent negative returns can be priced and is not diversified away. The reason for this is the investors' willingness to intentionally hold stocks that frequently demonstrate positive returns and to avoid stocks that frequently demonstrate negative returns. Additionally, the literature (Shleifer and Vishny (1997)) shows that limits to arbitrage might prevent arbitrageurs to correct the mispricing and hence idiosyncratic risk might be priced.

In our empirical analysis, we perform univariate portfolio sorts using monthly value-weighted returns from July 1963 through December 2018 for US-based common stocks trading on the NYSE, AMEX and NASDAQ with end-of-month stock prices of at least $1. We show that an FL strategy based on investing in stocks with the highest frequency of negative returns and simultaneously selling stocks with the lowest frequency of negative returns in the previous month unconditionally earns 7.2% p.a. Since we show that the performance of the FL strategy is not robust to several alternative empirical specifications, instead of a uniform weighting of daily returns, we use an exponential weighting that puts the greatest weight on the most recent observations. The constructed the WFL strategy achieves a profit of 11.9% p.a. In general, the performance of the WFL strategy is robust to a variety of risk factors and firms' characteristics, and economically significant. The superior performance of the WFL strategy compared to the FL strategy indicates that not only the frequency but also the timing of daily negative returns over the previous month is important.

We run Fama-MacBeth regressions and show that there is a positive relationship between the WFL measure and the cross-section of future stock returns controlling for a large set of explanatory variables. A one standard deviation increase in the WFL measure leads to about 3.6% p.a. increase in expected return, ceteris paribus. Furthermore, we show that these results cannot be explained by market microstructure effects based on cumulative-abnormal return (CAR) plots. Moreover, the results remain statistically significant even if the rebalancing of the portfolio takes place on an arbitrary day of the month (Tab. 21). Since our measure is based on the *counting* of daily negative returns over the past month and not on their magnitude, the performance of our strategy cannot be fully explained by momentum and short-term reversal, as we also demonstrate via dependent bivariate sorts. Additionally, since our measure naturally relates to skewness, we control for idiosyncratic and total skewness, as well as coskewness by performing dependent bivariate sorts. As a robustness check for the FL strategy, we also consider a longer portfolio formation period of 3, 6 and 12-months. However, the results already become statistically insignificant or even reverse sign when three months of data are considered for portfolio formation. This suggests that only one month of daily data is relevant for the construction of our measure.

Existing literature shows that more experienced investors make less behavioural errors compared to retail investors and use rather sophisticated trading strategies (Feng and Seasholes (2005), Dhar and Zhu (2006), Korniotis and Kumar (2010)). In order to determine whether our documented-abnormal returns depend on investor sophistication, we perform an independent-bivariate sort using the stock holdings of institutional and retail investors. We show that independent of the investor type, the return on the trading strategy based on the WFL measure is positive and statistically significant. However, the performance is stronger for stocks with a higher fraction of retail investors. This finding supports the idea that retail investors are more prone to rely on simple heuristics and are more exposed to binary bias that compresses the return distribution in two categories and hot-hand fallacy that distorts the expectations.

The contribution of our paper is threefold. First, our paper contributes to the discussion on the role of decision-making heuristics in financial markets (Tversky and Kahneman (1974)). We construct an empirical measure that is based on counting the number of negative daily returns over the past month. This measure reflects the idea that people possess binary thinking (Oskarsson et al. (2009), Isaac and Schindler (2014), Fisher and Keil (2018)) and therefore mentally represent the return being either positive or negative, without accounting for its magnitude. Second, we contribute to the research on beliefs formation. Complementing the existing literature on momentum and short-term reversal, we argue that investors not only use past month's aggregate performance but also take into consideration daily realizations of individual stock returns while forming the expectations. In line with the hot-hand fallacy (Gilovich et al. (1985)), the results suggest that stocks with a high frequency of negative daily returns will be considered inferior to stocks with high frequency of positive daily returns and are thus underpriced. Additionally, in accordance with existing literature (Malmendier and Nagel (2011), Malmendier and Nagel (2016), Nagel and Xu (2022)), we show that the most recent information is important in the belief formation process, which follows from the superior performance of the WFL measure relative to the FL strategy. Finally, by showing that the frequency of negative returns predicts future stock returns, we contribute to the asset pricing literature, specifically on factor pricing (Ross (1976)).

The paper is structured as follows. Sec. 2 describes the data and variables used for the study. Sec. 3 introduces definitions and methods that are relevant for measure and portfolio construction. Sec. 4 discusses the descriptive statistics for the equally and exponentially weighted frequency of loss measures and presents the performance of trading strategies as well as asset pricing tests. Sec. 5 contains the results of robustness checks of the strategy. Sec. 6 concludes.

2 Data

We use daily and monthly equity data from the Center for Research in Security Prices (CRSP) from July 1963 through December 2018. Each month, we include all US-based common stocks trading on the NYSE, AMEX and NASDAQ with the end-of-month stock price of at least $1. The total number of firm-month observations equals 2.9 million. In order to be included into portfolio sorting, we require the stock monthly data contain at least 15 days of returns. To ensure that results are not driven by micro-cap stocks, NYSE breakpoints are used for portfolio formation and data is winsorized at 0.5% and 99.5%. All results in the paper are reported for the value-weighted returns using market capitalization because of statistical reliability (Hou et al. (2020)). We also adjust the returns for delisting following Shumway (1997) and Beaver et al. (2007). In the rest of the paper, we report t-statistics estimated using adjusted standard errors with 6 lags and finite sample correction (Newey and West (1987)).

The data on Fama and French factors such as excess market return (MKT), size (SMB), book-to-market (HML), profitability (RMW) and investment (CMA), as well as momentum (MOM) and short-term reversal (STR) come from Kenneth French's website. The data on the quality factor (QUAL) are obtained from the AQR data library (Asness et al. (2019)). The q-factors and expected growth factor are retrieved from Hou-Xue-Zhang q-factors data library (Hou et al. (2015)). The mispricing factors are taken from the R.F. Stambaugh's website (Stambaugh and Yuan (2017)).

Liquidity factor data is from Pastor's website (Pástor and Stambaugh (2003)). To control for individual stocks' characteristics, we use the following variables for the individual stock i:

- *Market beta* ($BETA_i$) is the slope coefficient generated by a time-series regression of daily excess stock returns on daily excess market returns (MKT) over the past 12-months (Sharpe (1964) and Lintner (1975)).
- *Size* ($SIZE_i$) is the natural logarithm of market capitalisation in month t (Bali et al. (2011)).
- *Idiosyncratic volatility* ($IVOL_i$) is the standard deviation of residuals obtained from a time-series regression of daily excess stock returns on daily excess market returns (MKT), size (SMB) and value (HML) Fama-French factor returns over the month t (Ang et al. (2006)).
- *Highest monthly return* (MAX_i) is the average of five highest daily returns in each month t (Bali et al. (2011)).
- *Lowest monthly return* (MIN_i) is the average of five lowest daily returns in each month t (Bali et al. (2011)).
- *Total skewness* ($SKEW_i$) is the sample skewness of daily realised stock returns over the last five years (Arditti (1967)).
- *Idiosyncratic skewness* ($ISKEW_i$) is the sample skewness of the residuals obtained from a time-series regression of daily excess stock returns on daily excess market returns (MKT), size (SMB) and value (HML) Fama-French factor returns over the last five years (Mitton and Vorkink (2007)).
- *Coskewness* ($COSKEW_i$) is systematic skewness and is represented as a slope coefficient obtained from a time-series regression of daily excess stock returns on both the excess market returns (MKT) and squared excess market returns (MKT^2) over the last five years (Harvey and Siddique (2000)).
- *Illiquidity* ($ILLIQ_i$) is the Amihud's measure of illiquidity (Amihud (2002)).

- *Short-term reversal* (STR_i) is the return in month t (Jegadeesh (1990)).
- *Momentum* (MOM_i) is the 12-months cumulative return from *t-11* until *t-1* (Jegadeesh and Titman (1993)).

To investigate the portfolio holdings, we use data on stock ownership from Thomson Reuters from January 1997 until December 2018. The data consists of a granular equity ownership of various investor types which is then aggregated to three main categories: Institutions, Strategic Entities and Funds. For our analysis, the data on institutions and individual investor ownership is used. Individual investors are represented by individual wealthy investors.

3 Methodology

In this section, we present the methodology implemented in our research. We use an empirical analysis to investigate the role of the frequency of loss (FL) and the weighted frequency of loss (WFL) for the investors' behaviour. In Eqn. (3.1), we construct the WFL measure $f^w_{i,t}$ for the stock i and month t. Following the literature that discusses the decision-making heuristics and behavioural biases such as binary bias and hot-hand-fallacy, the measure is based on counting the number of daily negative returns in the previous month where we apply the exponential weighting with the largest weight to the most recent observation (Eqn. (3.2)). We take a simple counting measure as a better approximation of the investors' behaviour according to Ungeheuer and Weber (2021).

$$f^w_{i,t} = \sum_{j=1}^{M_{i,t}} \tilde{w}^i_{j,t} 1_{r_{i,j}<0}, \tag{3.1}$$

where $M_{i,t}$ is the number of days in month t available for company i, $1_{\{.\}}$ stands for the indicator function, $r_{i,j}$ is the j-th daily return of the stock i and $\tilde{w}^i_{j,t}$ is the relative weight of the return j of stock i in month t,

$$\tilde{w}^i_{j,t} = \frac{w^i_j}{\sum_{j=1}^{M_{i,t}} w^i_j}, \tag{3.2}$$

where $w_j = \exp[r(j-1)]$ and $r \approx 0.13$ is deduced from Da et al. (2021) and the same for all stocks. We rely on the literature that argues that people tend to pay more attention to the most recent events (Da et al. (2021)). Hence we use an exponential weighting for the past daily observations. According to Eqn. (3.2), the most recent return obtains the largest weight and the most distant return obtains the smallest weight. If weights are equal, we receive a measure similar to Neszveda (2019) with the only difference that Neszveda (2019) uses positive returns. The frequency of loss (FL) in this case is defined as:

$$f_{i,t} = \frac{\sum_{j=1}^{M_{i,t}} 1_{r_{i,j}<0}}{M_{i,t}}, \tag{3.3}$$

where $M_{i,t}$ is the number of days in month t available for company i, $1_{\{.\}}$ stands for the indicator function, $r_{i,j}$ is the j-th daily return of the stock i.

We use a univariate portfolio analysis technique in order to investigate the cross-sectional relationship between the stock expected returns and the frequency of loss measures (FL and WFL). The strategy based on the (weighted) frequency of loss is formed as follows. In the end of month t the investor sorts all available stocks based on the (weighted) frequency of negative returns. Portfolio 10 contains stocks that have the highest (weighted) frequency of loss in month t. Portfolio 1 contains stocks that have the lowest (weighted) frequency of loss in month t. Finally, the investor buys stocks in Portfolio 10 and sells stocks in Portfolio 1 (HML strategy). The holding period is 1 month. To measure the performance of the HML strategy, we compute the average of the time series. If this value is positive and significant, it indicates that on average the strategy delivers a positive return.

To reduce the problem of confounding effects, we control for various risk factors (e.g. FF3 (Fama and French (1993)), FF5 (Fama and French (2015)), FF6 (Fama and French (2018)), short-term reversal (Jegadeesh (1990)), momentum (Carhart (1997)), idiosyncratic skewness (Boyer et al. (2010)), coskewness (Harvey and Siddique (2000)), quality factor (Asness et al. (2019)), liquidity (Pástor and Stambaugh (2003)), q-factor (Hou et al. (2015))). The idea of this correction is simply to understand whether the observed return is driven by a required risk compensation. Thus, we regress returns of each portfolio on several risk factors. We perform the portfolio analysis and estimate the Jensen's alpha according to the following regression:

$$\boldsymbol{r}_k = \alpha_k + \mathbf{F}\boldsymbol{\beta}_k + \boldsymbol{\epsilon}_k, \tag{3.4}$$

where $\boldsymbol{r}_k \in \mathbb{R}^{T\times 1}$ is the return of portfolio k based on the frequency of loss measure discussed in Eqn. (3.1) or in Eqn. (3.3), $\boldsymbol{F} \in \mathbb{R}^{T\times N}$ is an $T \times N$-dimensional matrix of N risk factors, $\boldsymbol{\beta}_k \in \mathbb{R}^{N\times 1}$ regression coefficients of the risk factors of portfolio k and α_k is the Jensen's alpha of portfolio k.

4 Results

4.1 Descriptive Statistics

In this subsection, we analyse and compare the unconditional portfolio returns of the strategy based on the frequency of loss that uses equally weighted daily returns (FL) and frequency of loss that uses exponentially weighted daily returns (WFL) which are in detail described in Sec. 3. In Tab. 1, we provide the summary statistics of monthly value-weighted portfolio returns of FL and WFL strategies respectively. First, for both measures, returns monotonically increase from Portfolio 1 to Portfolio 10 in overall resulting in the positive return of the HML strategy. Although the returns are positive for all portfolios, the return of Portfolio 1 lacks statistical significance. Moreover, compared to the FL strategy (7.2% p.a.), the WFL strategy demonstrates a considerably higher return of 11.9% p.a that shows even a greater statistical significance (t-statistic equals 7.17). It speaks in favour of return weighting when constructing the FL measure. Volatility also increases monotonically with the portfolio rank and varies between 15.4% and 17.9% p.a. In general, returns are negatively skewed with the only exception for HML strategy and leptokurtic. The results for the FL strategy are completely in line with the results documented by Neszveda (2019) that suggests that an investor is rewarded for buying stocks with higher frequency of loss and selling stocks with lower frequency of loss. Nevertheless, the WFL strategy earns even a higher return, indicating that the recent returns play a larger role in predicting the future returns.

Table 1: Summary Statistics of Portfolio Monthly Value-Weighted Returns

Panel A: Frequency of Loss Estimated Using Equally Weighted Daily Returns

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	3.27	5.06	5.84	6.75	7.12	7.41	7.88	7.96	9.08	10.46	7.20
t-stat	1.58	2.48	2.80	3.21	3.39	3.53	3.66	3.62	3.93	4.45	4.51
SD	15.35	15.14	15.50	15.65	15.61	15.64	16.02	16.37	17.17	17.51	11.88
Skewness	-0.49	-0.53	-0.55	-0.52	-0.50	-0.41	-0.21	-0.22	-0.15	-0.24	0.59
Kurtosis	2.60	2.17	2.34	1.99	1.74	1.85	2.50	2.39	2.66	2.87	6.74

Panel B: Frequency of Loss Estimated Using Exponentially Weighted Daily Returns

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	0.60	3.82	5.71	6.97	6.72	7.84	8.68	9.87	11.38	12.49	11.90
t-stat	0.29	1.81	2.69	3.29	3.14	3.62	3.94	4.30	4.94	5.19	7.17
SD	15.39	15.72	15.75	15.76	15.94	16.11	16.37	17.07	17.13	17.91	12.34
Skewness	-0.61	-0.46	-0.52	-0.47	-0.56	-0.28	-0.41	-0.18	-0.31	-0.26	0.93
Kurtosis	2.28	1.63	1.88	2.06	1.92	1.64	2.12	2.69	2.89	2.95	5.35

This table represents mean, t-statistics, standard deviation, skewness, kurtosis of monthly excess returns of portfolio value-weighted returns of strategy based on FL and WFL measures. Mean and standard deviation are annualized and in percent. The sample period is from January 1963 to December 2018.

To understand the portfolio characteristics, Tab. 2 presents the average market beta (BETA), idiosyncratic volatility (IVOL), maximum (MAX) and minimum (MIN) daily returns, short-term reversal (STR), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskewness (COSKEW) with equity market and size (SIZE) of stocks allocated in the corresponding decile. There is no particular pattern between the maximum, minimum daily returns and the portfolio rank. However, there is observed an increasing relationship between idiosyncratic skewness, idiosyncratic volatility and portfolio decile. Interestingly, market beta decays with a rank suggesting that stocks that demonstrate high frequency of loss along with significant positive return (Tab. 1) also have a low correlation with the market. The short-term reversal demonstrates a strong decreasing pattern and Tab. 2 reveals that stocks in Portfolio 10 are small and illiquid. Similar patterns are observed for the frequency of loss based on the exponentially weighted daily returns. To ensure that the return of the FL and

WFL strategies cannot be explained by the short-term reversal or illiquidity, we implement the univariate and bivariate sorts and Fama-MacBeth regression analysis in the following subsections. Additionally, given the evidence of small stocks in Portfolio 10, we exclude micro-cap stocks as a part of the robustness test and report the results in Sec. 5. Moreover, in our analysis we use value-weighted returns and NYSE breakpoints that also account for the size effect.

Table 2: Summary Statistics for Decile Portfolios of Stocks sorted by FL and WFL measures

Panel A: Frequency of Loss Estimated Using Equally Weighted Daily Returns

	FL	STR	IVOL	BETA	MAX	MIN	ISKEW	COSKEW	ILLIQ	SIZE
P1	0.39	13.43	37.59	0.95	3.78	-2.54	0.46	-0.008	0.53	5.88
P2	0.45	9.11	39.08	0.94	3.76	-2.80	0.47	-0.009	0.77	5.66
P3	0.49	6.64	40.35	0.93	3.77	-2.97	0.49	-0.010	1.01	5.47
P4	0.52	4.76	41.42	0.91	3.79	-3.10	0.51	-0.011	1.24	5.31
P5	0.55	3.12	42.51	0.90	3.81	-3.22	0.53	-0.012	1.50	5.15
P6	0.58	1.50	43.60	0.88	3.83	-3.33	0.55	-0.013	1.81	4.98
P7	0.60	-0.07	44.65	0.87	3.85	-3.44	0.58	-0.013	2.12	4.82
P8	0.63	-1.73	45.66	0.84	3.86	-3.55	0.60	-0.015	2.45	4.64
P9	0.67	-3.70	46.57	0.82	3.82	-3.66	0.64	-0.016	2.82	4.41
P10	0.76	-6.72	43.95	0.70	3.18	-3.48	0.71	-0.018	3.17	3.88

Panel B: Frequency of Loss Estimated Using Exponentially Weighted Daily Returns

	WFL	STR	IVOL	BETA	MAX	MIN	ISKEW	COSKEW	ILLIQ	SIZE
P1	0.33	12.48	38.46	0.93	3.80	-2.59	0.48	-0.009	0.66	5.75
P2	0.42	7.94	40.11	0.93	3.80	-2.89	0.49	-0.010	0.95	5.53
P3	0.47	5.75	41.39	0.92	3.82	-3.05	0.51	-0.011	1.19	5.35
P4	0.51	4.02	42.30	0.90	3.83	-3.17	0.52	-0.011	1.46	5.20
P5	0.55	2.58	43.27	0.89	3.84	-3.27	0.54	-0.011	1.68	5.06
P6	0.58	1.25	44.06	0.88	3.85	-3.37	0.56	-0.012	1.94	4.94
P7	0.61	-0.13	44.96	0.86	3.86	-3.46	0.58	-0.013	2.20	4.79
P8	0.65	-1.47	45.57	0.84	3.84	-3.52	0.60	-0.014	2.47	4.63
P9	0.70	-3.15	46.08	0.81	3.76	-3.59	0.63	-0.016	2.66	4.43
P10	0.81	-6.19	42.74	0.69	3.05	-3.36	0.71	-0.018	2.94	3.89

This table represents characteristics of portfolios constructed based on the frequency of loss. The stocks characteristics are frequency of loss (FL) or weighted frequency of loss (WFL), short-term reversal (STR), idiosyncratic volatility (IVOL), market beta (BETA), daily maximum returns (MAX), daily minimum returns (MIN), idiosyncratic skewness (ISKEW), coskewness with equity market (COSKEW), Amihud's illiquidity measure (ILLIQ) and market capitalization (SIZE). STR, IVOL, MAX, and MIN are expressed as a percentage.

4.2 Frequency of Loss Based on Equally Weighted Sorting

We start with the analysis of the strategy that buys stocks with the high frequency of negative returns and simultaneously sells stocks with low frequency of negative returns according to Eqn. (3.3). Tab. 3 shows the results obtained from the time-series regression of portfolio returns based on the FL measure on risks factor returns that are widely used in the literature. The risk-adjusted returns of the FL strategy are estimated using the capital asset pricing model (CAPM), Fama-French three-factors (FF3), Fama-French three-factor model augmented with momentum factor of Carhart (1997) (FFC), Fama-French three-factor model augmented with momentum (Carhart (1997)) and liquidity (Pástor and Stambaugh (2003)) factors (FFCPS), and short-term reversal factor (STR) (Jegadeesh (1990)). The reported Jensen's alpha and the corresponding t-statistic indicate that even after controlling for risk factors, the return of the FL strategy remains positive and statistically significant. Jensen's alpha is monotonically increasing from Portfolio 1 to Portfolio 10, where the first three portfolios demonstrate, in general, a negative alpha. Confirming the results in Tab. 2 that there is a strong negative relationship between short-term reversal and the FL measure, Tab. 3 shows that STR can best explain the returns of the FL strategy compared to other models. However, the intercept is positive and statistically significant (t-statistic 2.23) resulting in an annual profit of 2.4%. These results suggest that an abnormal return of the FL strategy cannot be fully explained by risk factors.

Table 3: Univariate Portfolio Analysis - FL

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.27	0.42	0.49	0.56	0.59	0.62	0.66	0.66	0.76	0.87	0.6
	(1.6)	(2.34)	(2.63)	(3.02)	(3.18)	(3.32)	(3.49)	(3.52)	(3.84)	(4.18)	(5.05)
CAPM	-0.23	-0.09	-0.04	0.03	0.06	0.09	0.12	0.12	0.2	0.32	0.55
	(-4.15)	(-2.07)	(-1.2)	(0.71)	(1.6)	(2.29)	(2.88)	(2.28)	(2.96)	(3.9)	(4.87)
FF3	-0.19	-0.07	-0.03	0.03	0.05	0.07	0.08	0.07	0.14	0.21	0.4
	(-3.41)	(-1.49)	(-1)	(0.73)	(1.44)	(1.87)	(2.15)	(1.47)	(2.16)	(2.92)	(3.77)
FFC	-0.31	-0.13	-0.05	0.03	0.07	0.11	0.14	0.17	0.28	0.37	0.68
	(-5.69)	(-3.23)	(-1.3)	(0.81)	(1.96)	(2.89)	(3.21)	(3.09)	(3.93)	(4.77)	(6.12)
FFCPS	-0.33	-0.15	-0.04	0.05	0.08	0.1	0.15	0.18	0.3	0.37	0.7
	(-5.77)	(-3.33)	(-1.01)	(1.15)	(1.93)	(2.66)	(3.15)	(3.1)	(3.91)	(4.66)	(6.12)
STR	0.26	0.33	0.35	0.38	0.36	0.35	0.35	0.32	0.36	0.46	0.2
	(1.36)	(1.69)	(1.75)	(1.93)	(1.87)	(1.85)	(1.88)	(1.74)	(1.84)	(2.24)	(2.23)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

We have shown that none of the well-known risk factors can explain the significant excess return of the strategy based on the one month frequency of loss. We further analyse the sensitivity of the FL measure to the portfolio formation horizon, exclusion microcaps and exclusion of the last trading day in the month. We find that the results become insignificant even for the excess returns without risk corrections or subsumed by the STR factor.

First, we analyse how the measure is sensitive to the portfolio formation horizon. We consider a longer portfolio formation period, namely 3,6 and 12 months. The motivation for the consideration of the longer portfolio formation period is that one month measure could be a noisy estimator of the firm's feature and hence by using more data we can obtain a more precise estimator. The results presented in Tab. 4 show that unconditional excess returns become insignificant or even of the reverse sign when a longer portfolio formation horizon is considered. The risk-adjusted results for every estimation horizon are presented in App. A. The results suggest that abnormal returns of the FL strategy are driven by the recent performance that may indicate the overreaction to the recent observations as was already shown empirically (Da et al. (2021)).

Table 4: Univariate Portfolio Analysis for the FL strategy formed using 1, 3, 6 and 12 months of the daily data.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
FL 1 month	0.27	0.42	0.49	0.56	0.59	0.62	0.66	0.66	0.76	0.87	0.6
	(1.6)	(2.34)	(2.63)	(3.02)	(3.18)	(3.32)	(3.49)	(3.52)	(3.84)	(4.18)	(5.05)
FL 3 months	0.51	0.44	0.5	0.51	0.57	0.59	0.64	0.64	0.67	0.68	0.16
	(2.91)	(2.45)	(2.72)	(2.86)	(3.07)	(3.07)	(3.22)	(3.24)	(3.2)	(2.94)	(1.03)
FL 6 months	0.51	0.51	0.58	0.53	0.54	0.61	0.61	0.57	0.54	0.42	-0.09
	(2.76)	(2.84)	(3.24)	(2.81)	(2.76)	(3.15)	(3.24)	(2.91)	(2.55)	(1.82)	(-0.56)
FL 12 months	0.59	0.53	0.52	0.52	0.53	0.5	0.57	0.41	0.44	0.39	-0.2
	(3.06)	(2.9)	(2.98)	(3.05)	(2.98)	(2.65)	(2.98)	(2.04)	(2.09)	(1.55)	(-1.02)

This table shows portfolio raw excess returns for different formation horizons, namely 1,3, 6 and 12 months. The last column presents the average excess of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile.

Another possible reason for the lack of the significant risk-premia could be that the measure becomes less persistent that leads to the deterioration of the results. However, the persistence of the measure based on 1 month (correlation between t and $t+1$) equals 0.30, whereas the persistence of the measure based on 12 months (correlation between t and $t+12$) equals 0.63. This suggests that the measure based on more data is better in capturing the persistent characteristic of the firm, however, this characteristic is not priced.

Second, we analyse the sensitivity of the measure to exclusion of the last trading day. The motivation for this analysis arises from the previous evidence that using more data does not improve the measure's performance. Tab. 5 presents the excess returns of the FL strategy when the last trading day is excluded from the measure construction. We observe that the return for the HML strategy based on the unconditional excess returns decreases and becomes insignificant if we correct for the FF3 and STR. This suggests that the assumption that all days play the same importance for the measure construction is not supported by the data.

Table 5: Univariate Portfolio Analysis - the FL measure based on 1 months excluding the last day

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.36	0.45	0.5	0.54	0.57	0.64	0.67	0.62	0.67	0.77	0.41
	(2.15)	(2.45)	(2.67)	(2.83)	(3.03)	(3.49)	(3.67)	(3.27)	(3.36)	(3.6)	(3.36)
CAPM	-0.14	-0.07	-0.03	0	0.03	0.11	0.13	0.08	0.11	0.22	0.36
	(-2.58)	(-1.49)	(-0.74)	(-0.01)	(0.94)	(2.79)	(3.46)	(1.43)	(1.77)	(2.68)	(3.07)
FF3	-0.1	-0.04	-0.01	0.01	0.03	0.09	0.1	0.02	0.04	0.1	0.2
	(-1.88)	(-0.89)	(-0.28)	(0.16)	(0.87)	(2.38)	(2.66)	(0.41)	(0.69)	(1.45)	(1.93)
FFC	-0.22	-0.1	-0.03	0	0.05	0.13	0.16	0.12	0.17	0.25	0.47
	(-4.19)	(-2.31)	(-0.86)	(-0.03)	(1.51)	(3.41)	(4.11)	(2.15)	(2.92)	(3.2)	(4.22)
FFCPS	-0.23	-0.11	-0.02	0.02	0.06	0.13	0.16	0.12	0.18	0.26	0.49
	(-4.18)	(-2.44)	(-0.61)	(0.43)	(1.81)	(3.29)	(3.91)	(2.07)	(3.02)	(3.24)	(4.25)
STR	0.34	0.36	0.36	0.35	0.33	0.37	0.36	0.27	0.29	0.36	0.01
	(1.82)	(1.78)	(1.79)	(1.74)	(1.71)	(1.96)	(1.94)	(1.44)	(1.44)	(1.71)	(0.13)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)) excluding the last trading day. The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Third, we analyse whether the results remain significant if we exclude stocks with a small capitalisation. We use stocks traded on NYSE to determine the market capitalisation deciles and then define microcaps to be stocks that belong to the first two deciles. Then we exclude such stocks from the analysis and repeat the univariate portfolio exercises. Tab. 6 presents the excess returns of the FL strategy when microcaps are excluded from the analysis. We observe that the return for the HML strategy based on the unconditional excess returns remains positive, but becomes insignificant if we correct for the STR. This suggests that the previous results are more pronounced for small and illiquid stocks.

Table 6: Univariate Portfolio Analysis - the FL measure based on 1 months excluding microcaps

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.26	0.45	0.47	0.52	0.58	0.58	0.64	0.68	0.7	0.84	0.58
	(1.51)	(2.48)	(2.55)	(2.81)	(3.11)	(3.14)	(3.45)	(3.71)	(3.64)	(4.14)	(5.03)
CAPM	-0.24	-0.06	-0.05	-0.01	0.04	0.05	0.11	0.15	0.15	0.28	0.52
	(-4.35)	(-1.3)	(-1.29)	(-0.22)	(1.17)	(1.34)	(2.76)	(3.36)	(2.55)	(3.86)	(4.79)
FF3	-0.2	-0.03	-0.03	0	0.05	0.05	0.09	0.11	0.1	0.2	0.4
	(-3.57)	(-0.6)	(-0.71)	(0.12)	(1.23)	(1.25)	(2.4)	(2.53)	(1.74)	(2.9)	(3.76)
FFC	-0.33	-0.11	-0.06	0	0.06	0.07	0.13	0.18	0.21	0.36	0.69
	(-5.78)	(-2.41)	(-1.57)	(0.05)	(1.44)	(1.8)	(3.31)	(3.77)	(3.63)	(4.93)	(6.21)
FFCPS	-0.34	-0.13	-0.06	0.01	0.07	0.07	0.13	0.19	0.22	0.37	0.71
	(-5.79)	(-2.64)	(-1.47)	(0.37)	(1.6)	(1.74)	(3.26)	(3.74)	(3.66)	(4.88)	(6.2)
STR	0.25	0.37	0.35	0.36	0.36	0.33	0.35	0.37	0.33	0.41	0.16
	(1.31)	(1.86)	(1.76)	(1.84)	(1.89)	(1.75)	(1.9)	(1.99)	(1.75)	(2.08)	(1.82)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)) excluding microcaps. The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Overall, this evidence suggests that the FL measure is not robust to several alternative empirical specifications. The crucial assumption that the timing of the observations does not play a role is not supported by the data. The most recent observations are more important for the measure construction that support the evidence in the literature about the hot-hand fallacy (Gilovich et al. (1985)) and the recency bias (Nagel and Xu (2022), Malmendier and Nagel (2016)). In the next step we analyse the role of the overreaction to the most recent negative observations and examine portfolio holdings of institutional and retail investors. This leads us to the analysis of the weighted frequency of loss (WFL).

4.3 Frequency of Loss Based on Exponentially Weighted Sorting

Given the evidence that the strategy based on the frequency of loss earns high return, we continue with the analysis of the strategy that buys stocks with high frequency of recent negative returns and simultaneously sells stocks with low frequency of recent negative returns with a major difference that daily returns are exponentially weighted and the last observed return in month t receives the greatest weight (Eqn. (3.2)). Tab. 7 shows the results obtained from the time-series regression of WFL portfolio returns on risks factor returns that are widely used in the literature. The risk-adjusted returns of the WFL strategy are estimated using the capital asset pricing model (CAPM), Fama-French three-factors (FF3), Fama-French three-factor model augmented with momentum factor of Carhart (1997) (FFC), Fama-French three-factor model augmented with momentum (Carhart (1997)) and liquidity (Pástor and Stambaugh (2003)) factors (FFCPS), and short-term reversal factor (STR). The reported Jensen's alpha and the corresponding t-statistic indicate that even after controlling for risk factors, the return of the WFL strategy remains positive and statistically significant. Jensen's alpha is monotonically increasing from Portfolio 1 to Portfolio 10, where the first three portfolios have, in general, a negative alpha. Confirming the results in Tab. 2 that there is a strong negative relationship between short-term reversal and the WFL measure, Tab. 7 shows that STR can best explain the returns of the WFL strategy compared to other models. However, the intercept is positive and statistically significant (t-statistic 5.43) resulting in an annual profit of 7.56%. These results suggest that an abnormal return of the WFL strategy cannot be fully explained by risk factors. The reported alphas are greater than the one presented in Sec. 4.2 that again speaks in favour of return weighting when creating the strategy. Since the results might be subjected to specific firm's characteristics, we also control for quality, firm's investment behaviour and profitability (Tab. 11). Furthermore, we consider the mispricing factor proposed by Stambaugh and Yuan (2017).

Table 7: Univariate Portfolio Analysis - WFL

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.05	0.32	0.48	0.58	0.56	0.65	0.72	0.82	0.95	1.04	0.99
	(0.28)	(1.72)	(2.51)	(3.08)	(2.98)	(3.39)	(3.65)	(4.05)	(4.86)	(5.07)	(7.59)
CAPM	-0.44	-0.2	-0.05	0.05	0.03	0.12	0.18	0.27	0.4	0.48	0.92
	(-6.58)	(-3.87)	(-1.04)	(1.1)	(0.53)	(2.15)	(2.9)	(3.95)	(5.65)	(5.34)	(7.34)
FF3	-0.42	-0.19	-0.07	0.05	0.02	0.11	0.16	0.23	0.35	0.41	0.83
	(-6.25)	(-3.69)	(-1.39)	(1.03)	(0.31)	(2.09)	(2.72)	(3.54)	(5.21)	(4.72)	(6.6)
FFC	-0.52	-0.27	-0.12	0.05	0.04	0.16	0.2	0.32	0.45	0.56	1.08
	(-8.17)	(-5.02)	(-2.13)	(0.9)	(0.81)	(2.73)	(3.23)	(4.84)	(5.62)	(5.97)	(8.07)
FFCPS	-0.53	-0.28	-0.11	0.03	0.02	0.19	0.2	0.33	0.47	0.57	1.1
	(-7.81)	(-4.93)	(-1.89)	(0.61)	(0.3)	(3.12)	(3.18)	(4.66)	(5.68)	(5.75)	(7.8)
STR	0.01	0.22	0.34	0.4	0.32	0.42	0.44	0.51	0.6	0.64	0.63
	(0.07)	(1.09)	(1.68)	(1.95)	(1.57)	(2.15)	(2.15)	(2.54)	(3.08)	(3.14)	(5.43)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Along with the univariate analysis, we also conduct the bivariate dependent-sorting, where short-term reversal (STR), market beta (BETA), idiosyncratic volatility (IVOL), maximum (MAX) and minimum (MIN) daily returns, illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskewness (COSKEW) with equity market and size (SIZE) are used as control variables. This analysis is particularly important given a decreasing pattern between the weighted frequency of loss and the short-term reversal documented in Tab. 2. For the bivariate dependent-analysis, each month we first sort stocks into deciles based on their control variable (e.g. short-term reversal, idiosyncratic volatility, 12-month β, market capitalisation etc.). Then within each decile of the control variable we sort stocks in an ascending order based on their weighted frequency of loss. Tab. 8 shows that across all control variables, the average returns of the WFL decile portfolios increase monotonically with the portfolio rank. It results in a positive statistically significant return of the HML strategy. Only controlling for the short-term reversal significantly reduces the magnitude of the HML return from 0.99% reported in Tab. 7 to 0.8% per month. Moreover, even after additionally controlling for Fama-French four-factor returns, the difference in alphas on the on the portfolios with the high and low WFL measure remains positive and statistically significant. Hence, none of the analysed control variables can account for the difference in portfolio returns based on the weighted frequency of loss.

Table 8: Returns of Portfolios Sorted by weighted frequency of Loss Controlling for STR, MOM, IVOL, BETA, MAX, MIN, ISEW, COSKEW and ILLIQ

	STR	MOM	IVOL	BETA	MAX	MIN	ISKEW	COSKEW	ILLIQ
P1	0.16	-0.02	0.12	0.14	0.19	0.07	0.12	0.14	0.05
	(0.83)	(-0.09)	(0.67)	(0.75)	(1.09)	(0.35)	(0.66)	(0.78)	(0.25)
P2	0.37	0.27	0.3	0.39	0.35	0.28	0.31	0.32	0.32
	(2.03)	(1.34)	(1.6)	(2.08)	(1.96)	(1.35)	(1.65)	(1.7)	(1.62)
P3	0.47	0.38	0.41	0.42	0.47	0.44	0.5	0.44	0.43
	(2.58)	(1.86)	(2.2)	(2.28)	(2.64)	(2.18)	(2.65)	(2.3)	(2.21)
P4	0.58	0.49	0.47	0.54	0.47	0.58	0.53	0.62	0.54
	(3.13)	(2.35)	(2.46)	(2.9)	(2.46)	(2.85)	(2.87)	(3.22)	(2.77)
P5	0.66	0.51	0.59	0.65	0.61	0.59	0.57	0.59	0.66
	(3.6)	(2.39)	(3.06)	(3.33)	(3.11)	(2.9)	(3.03)	(2.96)	(3.31)
P6	0.72	0.67	0.72	0.68	0.64	0.77	0.7	0.73	0.75
	(4.04)	(3.13)	(3.73)	(3.49)	(3.29)	(3.77)	(3.56)	(3.63)	(3.76)
P7	0.75	0.79	0.77	0.77	0.75	0.86	0.78	0.76	0.87
	(4.05)	(3.56)	(3.92)	(3.85)	(3.64)	(4.22)	(3.97)	(3.7)	(4.41)
P8	0.88	0.97	0.96	0.84	0.89	0.93	0.85	0.87	0.92
	(4.78)	(4.25)	(4.78)	(4.06)	(4.07)	(4.47)	(4.21)	(4.07)	(4.55)
P9	0.92	1.04	1.03	1.05	1.03	1.07	1.03	1.05	1.05
	(5.1)	(4.66)	(5.24)	(5.04)	(4.74)	(5.21)	(5.16)	(4.82)	(5.27)
P10	0.96	1.21	1.23	1.17	1.17	1.25	1.16	1.12	1.3
	(5.19)	(5.1)	(5.99)	(5.49)	(5.16)	(6.04)	(5.7)	(5.11)	(6.31)
HML	0.8	1.23	1.11	1.04	0.98	1.18	1.05	0.98	1.25
	(7.47)	(9.7)	(9.55)	(8.61)	(7.3)	(10.82)	(7.74)	(7.77)	(11.42)
Alpha difference	0.87	1.22	1.14	1.06	0.98	1.21	1.12	1.06	1.34
	(8.15)	(9.53)	(9.98)	(8.77)	(8.25)	(11.89)	(8.34)	(8.52)	(10.53)

This table presents average monthly value-weighted returns of decile portfolios sorted by weighted frequency of loss after controlling for short-term reversal (STR), momentum (MOM), market beta (BETA), idiosyncratic volatility (IVOL), maximum (MAX) daily returns, minimum (MAX) daily returns, illiquidity (ILLIQ), idiosyncratic skewness (ISKEW) and coskewness (COSKEW) with equity market. "HML" is the average monthly return spread between High-WFL (10th decile) and Low-WFL (1st decile) portfolios. "Alpha difference" is the difference in Jensen's alphas between High-WFL and Low-WFL portfolios estimated in Fama-French four-factor model. The Newey-West t-statistics are estimated using 6 lags are reported in parentheses.

To estimate the cross-sectional price of the risk for the WFL measure, we proceed with the Fama-MacBeth regression (Fama and MacBeth (1973)). Namely, we perform monthly firm-level cross-sectional regressions of future stock excess returns in $t+1$ on the lagged explanatory variables in month t. First, a model using only the WFL measure as an explanatory variable is analysed (model 1 in Tab. 9), then the specification with the WFL measure in combination with another control variable is considered (models 2 to 10 in Tab. 9) and finally we examine the model that contains all ten explanatory variables (model 11 in Tab. 9). The independent variables are winsorized at 0.5%

and 99.5% level on a monthly basis. The general specification of the model has the following form:

$$R_{i,t+1} = \lambda_{0,t} + \beta_t WFL_{i,t} + \boldsymbol{\lambda}_t \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}, \tag{4.1}$$

where $R_{i,t+1}$ is the excess return of company i in month $t+1$, $\lambda_{0,t}$ is the intercept at time t, β_t is the regression coefficient of the WFL measure at time t, $\boldsymbol{X}_{i,t}$ is the vector of firm specific i variables at time t, namely: $STR_{i,t}$, $MOM_{i,t}$, $BETA_{i,t}$, $IVOL_{i,t}$, $MAX_{i,t}$, $ISKEW_{i,t}$, $COSKEW_{i,t}$, $SIZE_{i,t}$ and $ILLIQ_{i,t}$. The vector $\boldsymbol{\lambda}_t$ contains the regression coefficients of the firm specific variables $\boldsymbol{X}_{i,t}$ at time t.

Tab. 9 summarises the time-series averages of the slope coefficients and adjusted t-statistics estimated using six lags (Newey and West (1987)). The results in Tab. 9 indicate that there is a positive relationship between the weighted frequency of loss and the cross-section of future stock returns. The risk premium becomes even larger when all explanatory variables are taken into account, compared to the model (1) using only the WFL measure. The null hypothesis that the risk premium on the WFL measure equals zero can be rejected at the 1% level for all model specifications. Since the monthly cross-sectional standard deviation of the WFL measure equals 0.143, one standard deviation increase in the WFL measure leads to about 0.3% increase in expected return holding all other variables constant. Furthermore, given that the difference in the average WFL measure between stocks in the highest and the lowest decile equals 0.37 (Tab. 7), the difference in expected return between stocks in Portfolio 10 and Portfolio 1 risk varies between 0.8% and 0.9% per month depending on the specification. Interestingly, although the sign of the second variable is generally consistent with the literature, except for MOM and MAX, its average slope coefficient is indistinguishable from zero. When considering the full specification as defined in Eqn. (4.1), the slope coefficient on STR and ILLIQ flips the sign but still remains insignificant. Along with weighted frequency of loss, MOM, IVOL, ISKEW and SIZE demonstrate a significant average slope coefficient. The adjusted R^2 is at maximum for the full regression specification and reaches 13.5%. In total, these results provide clear evidence that the economically and statistically significant positive relationship between the weighted frequency of loss and future stock returns persists even after controlling for various firm's characteristics. It confirms that an WFL factor is priced in the cross-section of stock returns.

Table 9: Fama–MacBeth Regression Analysis - weighted frequency of Loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WFL	2.159	2.151	2.355	2.243	2.223	2.069	2.308	2.271	2.206	2.235	2.284
	(7.809)	(8.087)	(8.896)	(7.908)	(8.363)	(7.465)	(7.939)	(7.988)	(8.44)	(7.735)	(9.137)
STR		0.002									-0.008
		(0.325)									(-1.054)
MOM			0.008								0.008
			(3.178)								(3.576)
BETA				0.044							0.026
				(0.232)							(0.151)
IVOL					-0.007						-0.008
					(-1.441)						(-1.785)
MAX						-0.089					-0.064
						(-1.686)					(-1.02)
ISKEW							-0.054				-0.089
							(-1.047)				(-2.117)
COSKEW								-0.945			-0.041
								(-0.941)			(-0.048)
SIZE									-0.029		-0.105
									(-0.748)		(-2.663)
ILLIQ										-0.042	0.043
										(-1.064)	(1.191)
Intercept	-0.574	-0.587	-0.904	-0.677	-0.444	-0.328	-0.639	-0.629	-0.386	-0.617	0.394
	(-2.665)	(-2.721)	(-4.289)	(-3.193)	(-2.338)	(-1.695)	(-2.866)	(-2.842)	(-0.864)	(-2.798)	(1.008)
Adj. R^2	1.2	2.7	4.5	6	3.9	4.4	2	2.2	3.6	1.5	13.5

This table represents the average slope coefficients from the monthly cross-sectional regressions on the lagged weighted frequency of loss (WFL), short-term reversal (STR), momentum (MOM), market beta (BETA), idiosyncratic volatility (IVOL), maximum (MAX) daily returns, illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskewness (COSKEW) with equity market and size (SIZE). The first column (1) shows the results of the regression including solely the WFL measure as an explanatory variable. The regressions from (2) to (10) include additionally to the WFL measure a further explanatory variable. The regression (11) is estimated using all ten control variables. The Newey-West t-statistics estimated using 6 lags are reported in parentheses. The adjusted R^2 is in percent.

4.4 Cumulative abnormal returns

Next step is to analyze the daily performance of the HML strategy. We use the methodology introduced by MacKinlay (1997) to estimate the daily cumulative abnormal returns (CAR). The abnormal return $AR_{i,t}$ for a strategy i at time t equals

$$AR_{i,t} = R_{i,t} - \mathbb{E}_{t-1}[R_{i,t}], \tag{4.2}$$

where $R_{i,t}$ is the realised return of the strategy i at time t and $\mathbb{E}_{t-1}[R_{i,t}]$ is the expected portfolio returns of strategy i at time t using the information up to time $t-1$. The expected return is estimated using the Fama-French five-factor model augmented with short-term reversal and momentum factors.

$$\mathbb{E}_{t-1}[R_{i,t}] = \hat{\alpha}_{t-1,i} + \mathbf{RF}_t \hat{\boldsymbol{\beta}}_{t-1,i}, \tag{4.3}$$

where $\mathbf{RF}_t$ are the risk-factors and $\hat{\alpha}_{t-1,i}, \hat{\boldsymbol{\beta}}_{t-1,i}$ are the OLS estimates using the data up to time $t-1$. This means that we estimate the expected return using the data up to the month of the portfolio formation and estimate the daily abnormal return out-of-sample for the next month. The monthly sequence of the daily abnormal returns is based on the trading days, meaning that the first abnormal return is calculated for the first trading and not the calendar day. This allows us to calculate the average abnormal return for every trading day τ

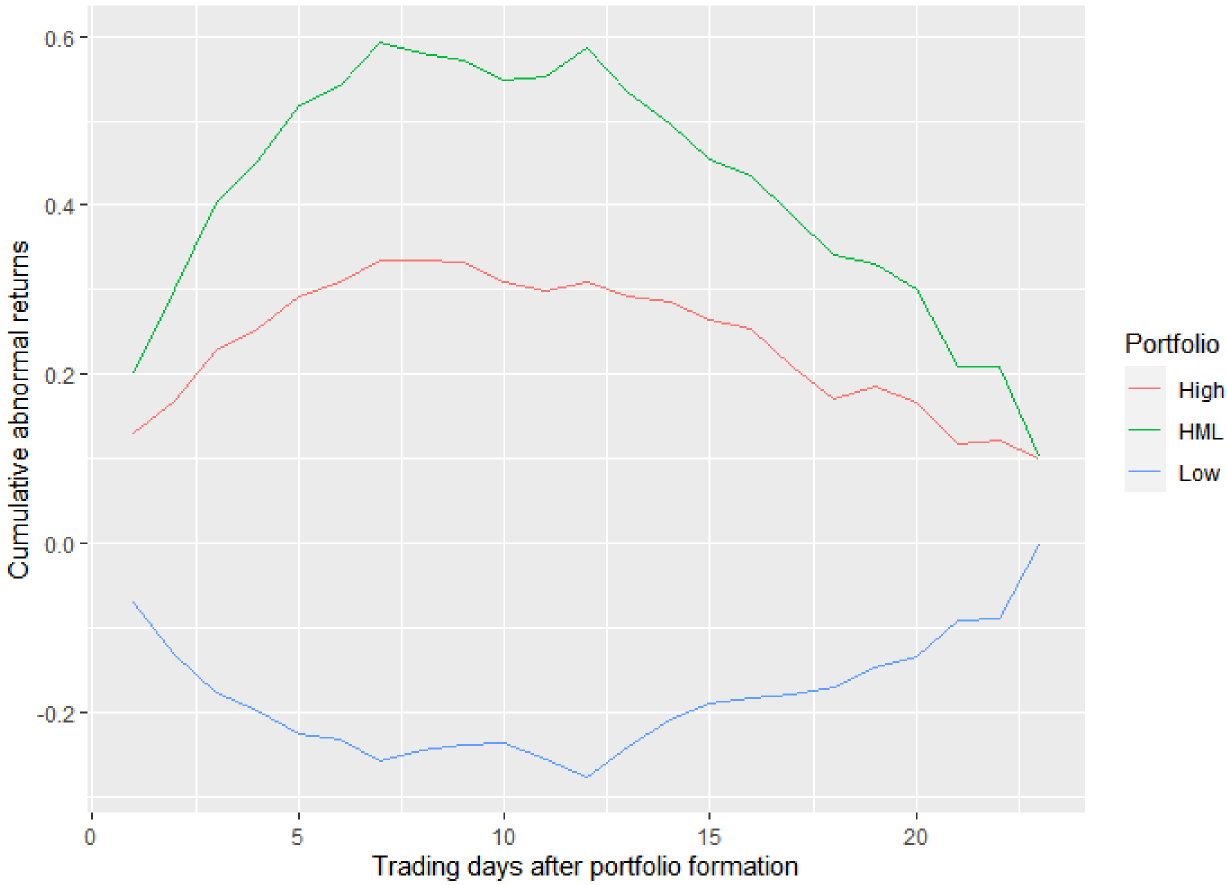
$$\bar{AR}_{i,\tau} = \frac{1}{T} \sum_{t=1}^{T} AR_{i,t}, \tag{4.4}$$

where T is the number of abnormal returns $AR_{i,t}$ for portfolio i at time t. Finally, we estimate the CAR

$$CAR_{i,M} = \sum_{\tau=1}^{M} \bar{AR}_{i,\tau}, \tag{4.5}$$

where M is the total number of trading days. Fig. 1 shows the $CAR_{i,m}$ where $m \in \{1, \ldots, M\}$ is the cumulative abnormal return up to the day m. Fig. 1 describes the performance of the HML strategy based on the weighted-frequency of loss over one month after portfolio formation. The CAR plot demonstrates that the abnormal HML returns are gradually accumulated over the first 12 days after portfolio formation and are not solely generated in the first days of the following month. The cumulative risk-adjusted returns suggest that the performance of the HML strategy is not subjected to the microstructure effects.

Figure 1: Daily Cumulative Abnormal Returns



4.5 Institutional Ownership

In this section, we analyse the institutional and retail stock ownership in order to examine whether stocks that have high frequency of negative returns are held by a particular investor type. On the one hand, there is literature that shows that individual investors prefer to invest in stocks that exhibit positive skewness (Kumar (2009), Bali et al. (2011)) and are even ready to hold the underdiversified portfolio to increase skewness of the total portfolio (Conine Jr and Tamarkin (1981), Calvet et al. (2007), Mitton and Vorkink (2007)). Thus, they select stocks that have a greater probability of very high payoff. Given the evidence of positive relationship between the weighted frequency of loss and idiosyncratic skewness in our data (Tab. 1), there might be a link between investor holdings and the performance of the HML strategy. On the other hand, since we assume a behavioural explanation of the performance of the HML strategy based on the weighted-frequency of loss, the propensity to invest in stocks with high frequency of recent negative returns might depend on the investor sophistication. It has been shown that sophisticated traders are less prone to behavioural biases and use complicated methods instead of simple heuristics when making investment decision (Dhar and Zhu (2006), Calvet et al. (2009), Bateman et al. (2016)).

In our paper, we are primarily interested in the institutional and retail ownership. However, we consider three groups of investors. They are institutional, retail investors and others. As according to the definition of Thomson Reuters, the institutions are presented by bank and trust, endowment funds, finance companies, foundations, government agencies, hedge funds, investment advisors, insurance companies, pension funds, private equity firms, venture capital firms, sovereign wealth funds and research firms. The data on institutional ownership is based not only on 13F filings but also on mutual fund aggregates and on declarable stakes. Thus, the ownership data is actualised on the monthly basis, and not quarterly as usually used in the literature. Since our data on retail investors is presented by individual wealthy investors, we can assume that this investor type can also have an impact on asset prices (Bali et al. (2020)). The ownership by the group "Others" is estimated as 100% less the institutional and retail ownership.

To examine the difference in holdings of stocks with respect to their measure of weighted frequency of loss between institutional and retail investors, we use the independent bivariate-sort. Namely, at the end of each month t, we independently sort all stocks in three portfolios based on their level of institutional or retail ownership and in five portfolios based on the ascending the WFL measure. As a result, 15 portfolios are created based on the intersection of ownership and the WFL measure groups. Tab. 10 reports the alpha for each portfolio relative to Fama-French four-factors. Portfolio INST3 (RETAIL3) contains stock with the highest institutional (retail) ownership. The last line of Tab. 10 shows the difference in excess returns between the quantile containing stocks with the highest WFL measure and the quantile containing stocks with the lowest WFL measure. Interestingly, the increasing pattern of alpha among the WFL measure groups persists almost for each level of ownership resulting in the positive excess return for HML strategy that remains statistically significant for both institutional and retail investors. Moreover, it is observed a decreasing pattern of HML alpha when institutional ownership is increasing, whereas the HML excess return increases with the level of retail ownership. For the quantile that includes stocks with the highest weighted frequency of loss, the portfolio where retail investors are more active earns 0.56% per month (t-statistic 2.04) vs. 0.19% per month (t-statistic 0.71) in portfolio where the fraction of institutional investors is the greatest. These results indicate that although the return of HML strategy is positive independent of the ownership, it is the largest for stocks that are held by retail investors.

Table 10: Bivariate Independent-Sort Portfolios Sorted by Ownership and the WFL measure

	INST1	INST2	INST3	RETAIL1	RETAIL2	RETAIL3
P1	-0.41	-0.2	-0.43	-0.36	-0.24	-0.3
	(-1.61)	(-1.21)	(-2.64)	(-2.14)	(-1.27)	(-1.24)
P2	-0.02	-0.2	0.55	0.58	-0.18	-0.05
	(-0.11)	(-1.18)	(2.68)	(2.86)	(-0.95)	(-0.3)
P3	0.16	0	-0.1	-0.03	0.07	0.1
	(0.82)	(0.02)	(-0.79)	(-0.22)	(0.34)	(0.49)
P4	0.17	0.24	-0.13	-0.06	0.09	0.29
	(0.94)	(1.24)	(-0.69)	(-0.26)	(0.41)	(1.34)
P5	0.44	0.45	0.19	0.22	0.3	0.56
	(1.57)	(2.24)	(0.71)	(0.85)	(1.27)	(2.04)
HML	0.87	0.71	0.6	0.56	0.6	0.88
	(2.56)	(2.85)	(1.89)	(2.02)	(1.93)	(2.51)

This table presents the average Jensen's alphas relative to the Fama-French four-factors for portfolios independently sorted by investor ownership and weighted frequency of loss (WFL). INST3 (RETAIL3) corresponds to the portfolio with highest institutional (retail) ownership. The data covers the period from January 1997 until December 2018. The Newey-West t-statistics estimated using 6 lags are reported in parentheses.

5 Robustness Checks

In this section, we examine the robustness of the portfolio returns based on the weighted frequency of loss. First, we analyse various factor models that are widely used in the literature. Second, we remove micro-caps stocks to ensure that results are not driven by outliers. Third, we consider a dataset that contains stocks traded only on NYSE. Finally, we consider the performance of the WFL strategy only for stocks that belong to the SP 500 index and if the transaction costs are included.

Additional to the risk factors considered in the Sec. 4.3, we analyse the performance of the WFL strategy that is based on Fama-French three-factor model augmented with the momentum factor of Carhart (1997), liquidity factor of Pástor and Stambaugh (2003) and the short-term reversal factor of (Jegadeesh (1990)) (FFCPS+STR), Fama-French five-factor model (FF5), Fama-French six-factor model (FF6), Fama-French six-factor model augmented with the liquidity factor of Pástor and Stambaugh (2003) (FF6PS) and short-term reversal factor of (Jegadeesh (1990)) (FF6PS+STR) and q-factor model Hou et al. (2015). Furthermore, in order to make sure that Portfolio 10 does not consist only of companies with unprofitable, stagnant or poorly-managed companies and Portfolio 1 includes profitable, growing and well-managed firms, we also control for the quality factor proposed by Asness et al. (2019) (QUAL). To control for the potential mispricing, the model using mispricing factor of Stambaugh and Yuan (2017) is analysed (Mispricing). We also conduct a regression where all available factors are included in the model (ALL).

Tab. 11 reports the risk-adjusted returns of portfolios sorted by WFL. The unconditional monthly excess returns and the corresponding t-statistics are reported in the first two lines of Tab. 11. Importantly, for each model, there is still observed a monotonic increasing alpha from Portfolio 1 to Portfolio 10. Furthermore, the alpha differences for the HML portfolio are all positive and highly statistically significant. The t-statistic ranges from 5.61 to 8.1. It confirms that the return obtained from investing in stocks with the high WFL measure and selling stocks with the low WFL measure cannot be completely explained by the risk factors.

Table 11: Univariate Portfolio Analysis - WFL Using Additional Risk Factors

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.05	0.32	0.48	0.58	0.56	0.65	0.72	0.82	0.95	1.04	0.99
	(0.28)	(1.72)	(2.51)	(3.08)	(2.98)	(3.39)	(3.65)	(4.05)	(4.86)	(5.07)	(7.59)
FF5	-0.49	-0.21	-0.11	0.04	0.03	0.1	0.2	0.26	0.37	0.47	0.96
	(-6.43)	(-3.37)	(-1.91)	(0.75)	(0.48)	(1.82)	(3.39)	(3.83)	(4.69)	(4.47)	(6.18)
FF6	-0.57	-0.28	-0.15	0.04	0.05	0.14	0.23	0.34	0.45	0.59	1.16
	(-8.08)	(-4.73)	(-2.49)	(0.7)	(0.88)	(2.47)	(3.78)	(5.01)	(5.58)	(6.1)	(8.1)
FF6PS	-0.58	-0.28	-0.13	0.02	0.02	0.17	0.24	0.35	0.48	0.61	1.19
	(-7.74)	(-4.62)	(-2.19)	(0.39)	(0.36)	(2.89)	(3.73)	(4.82)	(5.61)	(5.83)	(7.79)
FF6PS+STR	-0.42	-0.19	-0.07	0.04	-0.03	0.13	0.15	0.24	0.32	0.42	0.84
	(-5.75)	(-3.43)	(-1.33)	(0.65)	(-0.51)	(2.34)	(2.48)	(3.67)	(4.85)	(5.3)	(6.91)
FFCPS+STR	-0.39	-0.19	-0.06	0.05	-0.03	0.15	0.11	0.23	0.32	0.39	0.78
	(-5.63)	(-3.55)	(-1.06)	(0.88)	(-0.55)	(2.62)	(1.93)	(3.62)	(4.85)	(5.11)	(6.81)
Q	-0.6	-0.29	-0.15	0.05	0.07	0.17	0.24	0.35	0.48	0.61	1.21
	(-6.03)	(-3.66)	(-2)	(0.88)	(1.17)	(2.59)	(3.03)	(4.33)	(4.69)	(4.67)	(5.85)
SKEW	0.05	0.35	0.51	0.57	0.54	0.71	0.73	0.82	0.99	1.09	1.04
	(0.28)	(1.82)	(2.65)	(2.99)	(2.76)	(3.53)	(3.57)	(3.87)	(4.77)	(4.99)	(7.32)
COSKEW	0.04	0.35	0.52	0.57	0.55	0.71	0.74	0.82	0.99	1.1	1.06
	(0.23)	(1.75)	(2.55)	(2.82)	(2.71)	(3.4)	(3.48)	(3.76)	(4.78)	(5.02)	(7.71)
QUAL	0.38	0.7	0.85	0.98	0.98	1.05	1.16	1.27	1.4	1.54	1.16
	(2.55)	(4.63)	(5.37)	(6.37)	(6.55)	(6.33)	(7.36)	(7.55)	(8.19)	(9.02)	(7.94)
Mispricing	-0.61	-0.3	-0.12	0.02	0.06	0.19	0.25	0.36	0.5	0.63	1.24
	(-7.3)	(-4.68)	(-1.92)	(0.42)	(0.98)	(3.17)	(3.89)	(5.09)	(5.8)	(6.56)	(7.99)
ALL	-0.41	-0.16	-0.04	0.02	-0.02	0.13	0.16	0.17	0.28	0.38	0.79
	(-4.89)	(-2.87)	(-0.79)	(0.39)	(-0.38)	(2.2)	(2.5)	(2.48)	(3.47)	(4.45)	(5.61)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Next, we exclude the micro-cap stocks. As in Fama and French (2008), the micro-cap stocks are defined as those that are below the 20th NYSE market capitalization percentile. Tab. 12 shows that portfolio characteristics almost do not change when micro-cap stocks are excluded. The average returns increase with the portfolio rank. The returns of the first portfolio become even smaller and are indistinguishable from zero. Therefore, the return of HML portfolio becomes slightly larger than in Tab. 2. Furthermore, there is no significant difference in volatility, skewness or kurtosis among the portfolios compared to the case when the complete data is considered. In contrast to the frequency of loss measure (FL), where results become insignificant after controlling for the STR as soon as the micro-stocks are not considered, Tab. 13 shows that the returns of portfolios sorted based on the weighted frequency of loss remain positive and statistically significant. Thus, this provides evidence that our results are robust to the exclusion of micro-cap stocks.

Table 12: Summary Statistics of Monthly Value-Weighted Returns of Portfolios Sorted by Weighted Frequency of Loss when Micro-Cap Stocks are Excluded

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	0.08	4.15	5.01	6.58	6.51	7.23	7.77	9.49	10.85	12.45	12.37
t-stat	0.04	1.95	2.37	3.10	3.06	3.40	3.51	4.31	4.79	5.25	7.59
SD	15.39	15.85	15.72	15.79	15.86	15.83	16.44	16.39	16.85	17.65	12.13
Skew	-0.57	-0.52	-0.45	-0.45	-0.58	-0.39	-0.35	-0.41	-0.16	-0.24	0.84
Kurt	2.18	1.87	1.67	1.87	2.04	1.55	1.65	2.04	2.59	2.85	5.22

This table shows mean, t-statistics, standard deviation, skewness, kurtosis of monthly excess returns of portfolio value-weighted returns of strategy based on the WFL measure using the subsample of data excluding the micro-cap stocks. Mean and standard deviation are annualized and in percent. The sample period is from January 1963 to December 2018.

Table 13: Univariate Portfolio Analysis - WFL without Consideration of Micro-Cap Stocks

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
CAPM	-0.48	-0.17	-0.1	0.02	0.02	0.08	0.1	0.25	0.36	0.48	0.96
	(-6.92)	(-3.02)	(-1.88)	(0.35)	(0.31)	(1.5)	(1.66)	(4.26)	(4.9)	(6.02)	(7.8)
FF3	-0.47	-0.14	-0.12	0.02	0.01	0.08	0.08	0.23	0.33	0.42	0.89
	(-6.62)	(-2.51)	(-2.06)	(0.31)	(0.15)	(1.49)	(1.42)	(3.94)	(4.75)	(5.29)	(7.01)
FFC	-0.57	-0.24	-0.17	0	0.01	0.13	0.11	0.29	0.41	0.57	1.14
	(-8.39)	(-4.12)	(-2.84)	(0.06)	(0.13)	(2.35)	(1.69)	(5.01)	(5.5)	(6.35)	(8.36)
FFCPS	-0.58	-0.26	-0.15	0	-0.04	0.14	0.14	0.29	0.43	0.59	1.17
	(-8.03)	(-4.31)	(-2.4)	(0.05)	(-0.57)	(2.44)	(1.99)	(4.8)	(5.35)	(6.32)	(8.21)
STR	-0.03	0.27	0.29	0.38	0.34	0.34	0.39	0.51	0.59	0.64	0.66
	(-0.14)	(1.32)	(1.48)	(1.86)	(1.62)	(1.84)	(1.94)	(2.5)	(3.07)	(3.25)	(5.74)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for Fama-French, liquidity and short-term reversal factors when micro-stocks are excluded in the analysis (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Finally, we conduct the portfolio analysis using only the NYSE stocks, since they are likely to have less noisy returns. Tab. 14 shows that the excess return increases with the rank of the portfolio, resulting in a return of 12.16% p.a. for the HML strategy. Furthermore, the patterns observed in Sec. 4.3 persist also for stocks that are only traded on NYSE (Tab. 15). These results again speak for the robustness of strategy performance and for a general pattern in the stock market that does not depend on a specific stock exchange.

Table 14: Summary Statistics of Monthly Value-Weighted Returns of Portfolios Sorted by weighted frequency of Loss Exclusively Using Stocks Traded on NYSE

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	0.96	4.14	5.67	7.04	6.34	7.43	8.44	10.03	11.83	13.12	12.16
t-stat	0.48	2.03	2.75	3.43	3.07	3.55	3.98	4.53	5.31	5.40	6.92
SD	14.88	15.15	15.38	15.24	15.38	15.56	15.76	16.45	16.59	18.06	13.07
Skew	-0.61	-0.49	-0.49	-0.44	-0.47	-0.16	-0.34	0.01	-0.23	0.01	1.15
Kurt	2.24	1.82	1.90	2.43	2.03	1.65	2.26	3.63	3.21	3.97	8.68

This table shows the mean, t-statistics, standard deviation, skewness and kurtosis of the monthly excess returns of the value-weighted portfolio returns of the WFL-based strategy using the subsample of data comprising only NYSE-traded stocks. Mean and standard deviation are annualized and in percent. The sample period is from January 1963 to December 2018.

Table 15: Univariate Portfolio Analysis - WFL Only Using NYSE Traded Stocks

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
CAPM	-0.39	-0.15	-0.03	0.09	0.03	0.11	0.19	0.31	0.47	0.55	0.94
	(-5.06)	(-2.14)	(-0.46)	(1.32)	(0.41)	(1.98)	(2.6)	(3.89)	(5.06)	(5.15)	(6.83)
FF3	-0.4	-0.18	-0.09	0.04	-0.03	0.06	0.11	0.22	0.37	0.43	0.83
	(-5.15)	(-2.91)	(-1.47)	(0.7)	(-0.57)	(0.89)	(1.74)	(3.2)	(4.87)	(4.41)	(6.19)
FFC	-0.49	-0.23	-0.12	0.04	0.02	0.11	0.14	0.31	0.46	0.61	1.1
	(-6.85)	(-3.76)	(-1.88)	(0.73)	(0.36)	(1.68)	(2.1)	(4.49)	(5.13)	(5.51)	(7.45)
FFCPS	-0.5	-0.25	-0.12	0.02	-0.01	0.13	0.14	0.32	0.49	0.63	1.13
	(-6.55)	(-3.79)	(-1.81)	(0.4)	(-0.22)	(2)	(1.94)	(4.34)	(5.14)	(5.33)	(7.23)
STR	0.03	0.22	0.33	0.41	0.29	0.39	0.43	0.54	0.67	0.69	0.66
	(0.17)	(1.16)	(1.7)	(2.2)	(1.53)	(2.16)	(2.24)	(2.81)	(3.52)	(3.69)	(4.96)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for Fama-French, liquidity and short-term reversal factors using the subsample of data comprising only NYSE-traded stocks (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Furthermore, we analyse the performance of the WFL strategy only for stocks that are members of the S&P 500. The data on S&P 500 constituents comes from Wharton Research Data Services (WRDS) and covers period from December 1969 until December 2018. Tab. 17 shows that the return of the HML strategy is even higher for stocks included in S&P 500 than for the total set of stocks. By implementing the HML strategy, the investor would earn 1.14% per month or 13.7% per year. The results remain positive and statistically significant after controlling for various risk factors.

Since the strategy of selling Portfolio 1 and buying Portfolio 10 involves high portfolio turnover (Tab. 16), we analyse the performance of the WFL strategy after transaction costs. To estimate transaction costs, we retrieve the closing bid and ask prices for each S&P 500 stock for the last trading day of each month from the CRSP database. For each stock i at time t, the bid-ask spread is estimated as in Stoll and Whaley (1983):

$$Spread_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{(Ask_{i,t} + Bid_{i,t})/2}$$

.

By combining the turnover ratio and the bid-ask spread (Da et al. (2014)), the transaction cost for the WFL strategy equals $46 \times 88.20\% + 34 \times 90.20\% = 70.71$ basis points per month, resulting in the positive and statistically significant alpha of 0.42% (t-value of 1.89) of the WFL strategy.

Table 16: Summary Statistics of Monthly Value-Weighted Returns of S&P 500

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	0.07	0.56	0.58	0.51	0.64	0.71	0.68	0.90	0.97	1.19	1.12
t-stat	0.27	2.30	2.34	2.01	2.63	2.94	2.63	3.46	3.57	4.08	4.88
SD	4.25	4.29	4.40	4.44	4.28	4.28	4.58	4.57	4.78	5.15	4.07
Skew	-0.82	-0.31	-0.76	-0.53	-0.79	-0.55	-0.65	-0.46	-0.60	-0.3	1.08
Kurt	2.04	0.87	1.47	1.37	1.82	1.62	1.62	1.44	1.87	2.67	6.98
Turnover	90.20	89.90	90.10	89.70	89.46	89.36	90.00	89.60	89.40	88.20	
Spread	0.34	0.39	0.41	0.44	0.44	0.44	0.485	0.48	0.47	0.46	

This table represents mean, t-statistics, standard deviation, skewness, kurtosis of monthly excess returns of portfolio value-weighted returns of strategy based on the WFL measure using the subsample of data comprising only S&P 500-traded stocks. The last column presents the average excess returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags. Mean, standard deviation, portfolio turnover and bid-ask spread are in percent. The sample period is from January 1992 to December 2018.

Table 17: Univariate Portfolio Analysis - WFL Only Using S&P 500 Stocks

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.03	0.43	0.51	0.42	0.54	0.58	0.62	0.83	0.98	1.17	1.14
	(0.17)	(2.2)	(2.51)	(2.05)	(2.8)	(2.93)	(2.84)	(3.88)	(4.64)	(5.56)	(7.19)
CAPM	-0.45	-0.07	0	-0.11	0.02	0.06	0.08	0.29	0.43	0.6	1.05
	(-5.1)	(-0.91)	(0.05)	(-1.6)	(0.3)	(0.78)	(1.01)	(3.7)	(4.57)	(5.58)	(6.67)
FF3	-0.46	-0.07	-0.03	-0.15	0.03	0.03	0.07	0.26	0.41	0.52	0.98
	(-5.01)	(-0.97)	(-0.38)	(-2.19)	(0.44)	(0.42)	(0.9)	(3.4)	(4.76)	(5.04)	(6.24)
FFC	-0.55	-0.14	-0.09	-0.13	0.03	0.09	0.12	0.35	0.48	0.7	1.25
	(-6.86)	(-1.99)	(-1.03)	(-1.71)	(0.46)	(1.11)	(1.46)	(4.73)	(5.35)	(6.1)	(7.62)
FFCPS	-0.56	-0.15	-0.09	-0.11	0.03	0.07	0.11	0.34	0.47	0.69	1.25
	(-6.88)	(-2.09)	(-0.99)	(-1.53)	(0.39)	(0.95)	(1.25)	(4.67)	(5.34)	(6.19)	(7.77)
STR	0.01	0.35	0.39	0.24	0.34	0.35	0.4	0.57	0.69	0.78	0.77
	(0.04)	(1.65)	(1.83)	(1.18)	(1.66)	(1.74)	(1.87)	(2.63)	(3.41)	(3.88)	(5.35)
FF5	-0.54	-0.14	-0.1	-0.19	-0.01	-0.02	0.05	0.26	0.42	0.54	1.08
	(-5.73)	(-1.74)	(-1.19)	(-2.65)	(-0.21)	(-0.31)	(0.56)	(3.11)	(4.72)	(4.34)	(6.11)
FF6	-0.61	-0.19	-0.14	-0.17	-0.01	0.03	0.09	0.33	0.47	0.68	1.29
	(-7.16)	(-2.58)	(-1.6)	(-2.23)	(-0.13)	(0.33)	(1.07)	(4.25)	(5.24)	(5.81)	(7.78)
FF6PS	-0.62	-0.2	-0.14	-0.16	-0.01	0.01	0.08	0.32	0.47	0.67	1.29
	(-7.15)	(-2.67)	(-1.54)	(-2.07)	(-0.18)	(0.18)	(0.88)	(4.21)	(5.26)	(5.89)	(7.91)
FF6PS_STR	-0.47	-0.11	-0.09	-0.14	-0.04	-0.03	0.05	0.26	0.36	0.48	0.95
	(-5.27)	(-1.5)	(-0.95)	(-1.84)	(-0.55)	(-0.4)	(0.55)	(3.23)	(4.37)	(5.73)	(7.18)
FFCPS_STR	-0.42	-0.06	-0.04	-0.09	0	0.03	0.08	0.28	0.38	0.51	0.93
	(-4.99)	(-0.9)	(-0.43)	(-1.33)	(0.05)	(0.42)	(0.96)	(3.66)	(4.47)	(6.11)	(7.15)
Q	-0.71	-0.21	-0.17	-0.24	-0.03	0.09	0.04	0.28	0.44	0.64	1.34
	(-6.24)	(-2.39)	(-1.62)	(-2.71)	(-0.33)	(0.99)	(0.38)	(3.39)	(4.15)	(4.51)	(6.13)
SKEW	-0.01	0.44	0.5	0.41	0.51	0.56	0.59	0.79	0.96	1.18	1.19
	(-0.07)	(2.16)	(2.34)	(1.94)	(2.52)	(2.74)	(2.65)	(3.57)	(4.42)	(5.39)	(7.3)
COSKEW	0	0.45	0.51	0.42	0.51	0.57	0.6	0.8	0.97	1.18	1.18
	(-0.01)	(2.22)	(2.45)	(2.05)	(2.65)	(2.83)	(2.72)	(3.75)	(4.67)	(5.66)	(7.52)
Qual	0.32	0.75	0.85	0.77	0.9	0.94	1	1.21	1.35	1.63	1.31
	(1.87)	(4.4)	(4.74)	(4.31)	(5.51)	(5.3)	(5.15)	(6.54)	(7.24)	(8.72)	(7.31)
Mispricing	-0.67	-0.21	-0.19	-0.16	0	0.05	0.06	0.3	0.49	0.7	1.37
	(-6.26)	(-2.97)	(-1.87)	(-1.95)	(-0.06)	(0.56)	(0.75)	(3.68)	(4.9)	(5.97)	(7.33)
ALL	-0.47	-0.11	-0.11	-0.13	-0.05	-0.05	0	0.19	0.29	0.39	0.86
	(-4.39)	(-1.58)	(-1.26)	(-1.65)	(-0.73)	(-0.59)	(0)	(2.24)	(2.9)	(4.42)	(5.88)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors in case when only stocks in S&P 500 are considered in the analysis (Eqn. (3.4)). The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high WFL in the 10th decile and sells stocks with low WFL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

6 Conclusion

In this paper, we empirically show that stocks that demonstrate a higher frequency of negative returns in the previous month earn a higher return in the next period. A strategy that is based on buying stocks with higher frequency of negative returns and selling stock with lower frequency of negative returns unconditionally earns a statistically significant positive return of 7.2% p.a. However, compared to the previous research, we show that the performance of this strategy is not robust to several alternative specifications. The results evaporate as soon as the longer portfolio formation period is considered, the last day or microcaps are excluded. Furthermore, by using the exponential weighting of daily returns that sets the greatest weight on the last daily observations, we show that the WFL strategy earns 11.9% p.a. and is robust to risk factors, firm characteristics, and alternative specifications. It suggests that the most recent information is important in the belief formation process, which follows from the superior performance of the WFL strategy relative to the FL strategy. The factor based on the WFL measure is priced across U.S. stocks.

Our findings highlight the role of heuristics in financial markets. Specifically, we show that the sign of the return and not only its magnitude is relevant for the investor in the decision-making process. This supports the idea that people possess binary thinking and therefore mentally represent the return being either positive or negative, without accounting for its size. Complementing the existing literature on momentum and short-term reversal, we argue that investors not only use past month's aggregate performance but also take into consideration daily realizations of individual stock returns while forming expectations. In line with the hot-hand fallacy, our findings support the idea that the frequency of past negative returns influences the expectations of investors affecting future company performance. Investor expectations about the fundamentals of the firm are distorted by the high frequency of recent negative returns that leads to an excessive selling of the stock. This results in the stock undervaluation inducing mispricing. According to the CAR plot, the results are not driven by the market microstructure. Furthermore, we show that the return of the strategy is larger for the stocks that are mostly held by retail investors. Therefore, this phenomenon can be related to investor sophistication. It speaks in favour of the existing theory that unsophisticated investors suffer more from recency bias and errors in the expectation formation process, and tend to use simple heuristics when making investment decisions.

In total, our paper confirms the importance of simple heuristics in understanding investment behaviour and belief formation. It supports the evidence of the existence of behavioural biases in the stock market, especially among non-professionals.

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A Appendix

Table 18: Univariate Portfolio Analysis - FL 3 months

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.51	0.44	0.5	0.51	0.57	0.59	0.64	0.64	0.67	0.68	0.16
	(2.91)	(2.45)	(2.72)	(2.86)	(3.07)	(3.07)	(3.22)	(3.24)	(3.2)	(2.94)	(1.03)
CAPM	0.02	-0.07	-0.02	-0.01	0.04	0.05	0.09	0.11	0.13	0.12	0.1
	(0.3)	(-1.53)	(-0.53)	(-0.29)	(0.77)	(1.04)	(1.53)	(1.6)	(1.42)	(1.07)	(0.62)
FF3	0.09	-0.03	-0.03	-0.04	-0.01	-0.01	0.02	0.02	0.01	-0.02	-0.11
	(1.49)	(-0.74)	(-0.69)	(-1.03)	(-0.12)	(-0.16)	(0.36)	(0.3)	(0.17)	(-0.19)	(-0.75)
FFC	-0.12	-0.14	-0.07	-0.02	0.08	0.11	0.18	0.21	0.25	0.29	0.41
	(-2.29)	(-3.27)	(-1.74)	(-0.5)	(1.65)	(2.3)	(3.02)	(3.66)	(2.96)	(2.81)	(2.95)
FFCPS	-0.14	-0.13	-0.08	-0.04	0.08	0.13	0.21	0.23	0.28	0.29	0.44
	(-2.63)	(-2.93)	(-1.75)	(-1)	(1.5)	(2.57)	(3.47)	(3.88)	(3.19)	(2.75)	(3.04)
STR	0.48	0.32	0.32	0.29	0.3	0.31	0.34	0.31	0.29	0.28	-0.21
	(2.44)	(1.66)	(1.66)	(1.56)	(1.63)	(1.58)	(1.66)	(1.58)	(1.42)	(1.18)	(-1.44)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)) based on 3 months. The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Table 19: Univariate Portfolio Analysis - FL 6 months

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.51	0.51	0.58	0.53	0.54	0.61	0.61	0.57	0.54	0.42	-0.09
	(2.76)	(2.84)	(3.24)	(2.81)	(2.76)	(3.15)	(3.24)	(2.91)	(2.55)	(1.82)	(-0.56)
CAPM	0.01	0	0.07	0.01	0.01	0.09	0.08	0.04	0	-0.12	-0.13
	(0.1)	(0.04)	(1.5)	(0.16)	(0.18)	(1.41)	(1.17)	(0.47)	(-0.05)	(-0.98)	(-0.78)
FF3	0.09	0.04	0.07	-0.03	-0.05	0	-0.01	-0.08	-0.14	-0.28	-0.37
	(1.45)	(0.84)	(1.51)	(-0.71)	(-0.94)	(-0.03)	(-0.13)	(-1.09)	(-1.78)	(-2.78)	(-2.66)
FFC	-0.16	-0.05	0.03	0.02	0.07	0.15	0.22	0.21	0.18	0.01	0.17
	(-2.57)	(-1.13)	(0.65)	(0.34)	(1.2)	(2.74)	(3.18)	(2.43)	(2.02)	(0.07)	(1.1)
FFCPS	-0.18	-0.05	0.01	0.01	0.07	0.16	0.25	0.23	0.19	-0.02	0.16
	(-2.77)	(-1.15)	(0.27)	(0.21)	(1.27)	(2.7)	(3.53)	(2.55)	(2.08)	(-0.14)	(1.03)
STR	0.45	0.36	0.4	0.29	0.28	0.34	0.3	0.23	0.19	0.06	-0.39
	(2.22)	(1.89)	(2.12)	(1.51)	(1.43)	(1.73)	(1.64)	(1.2)	(0.87)	(0.24)	(-2.48)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)) based on 6 months.. The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Table 20: Univariate Portfolio Analysis - FL 12 months

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Excess Return	0.59	0.53	0.52	0.52	0.53	0.5	0.57	0.41	0.44	0.39	-0.2
	(3.06)	(2.9)	(2.98)	(3.05)	(2.98)	(2.65)	(2.98)	(2.04)	(2.09)	(1.55)	(-1.02)
CAPM	0.09	0.03	0.03	0.02	0.03	-0.01	0.06	-0.1	-0.08	-0.14	-0.23
	(1.23)	(0.57)	(0.61)	(0.31)	(0.43)	(-0.07)	(0.83)	(-1.26)	(-0.79)	(-0.94)	(-1.16)
FF3	0.2	0.06	0.01	-0.03	-0.04	-0.12	-0.06	-0.26	-0.25	-0.38	-0.57
	(3.12)	(1.24)	(0.28)	(-0.5)	(-0.7)	(-1.83)	(-1)	(-3.64)	(-2.88)	(-3.26)	(-3.7)
FFC	-0.06	-0.04	0.04	0.04	0.09	0.07	0.16	-0.01	0.08	-0.05	0.01
	(-1.06)	(-0.82)	(0.89)	(0.66)	(1.33)	(1.06)	(2.35)	(-0.11)	(0.84)	(-0.46)	(0.04)
FFCPS	-0.07	-0.06	0.06	0.05	0.1	0.07	0.17	0.01	0.1	-0.09	-0.01
	(-1.29)	(-1.32)	(1.21)	(0.82)	(1.39)	(0.95)	(2.48)	(0.17)	(0.97)	(-0.73)	(-0.09)
STR	0.51	0.37	0.32	0.31	0.27	0.22	0.28	0.1	0.09	0.04	-0.46
	(2.39)	(1.88)	(1.78)	(1.78)	(1.44)	(1.16)	(1.45)	(0.49)	(0.43)	(0.17)	(-2.44)

This table shows portfolio raw excess returns in the first row and Jensen's alphas when controlling for various risk factors (Eqn. (3.4)) based on 12 months. The last column presents the average excess and risk-adjusted returns of the high-minus-low strategy (HML) that buys stocks with high FL in the 10th decile and sells stocks with low FL in the 1st decile. The corresponding Newey-West t-statistics are presented in parentheses and are adjusted using six lags.

Table 21: Summary Statistics of Monthly Value-Weighted Returns of the WFL strategy

Panel A: Portfolio Rebalancing takes place on the First Trading Day of Month

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	1.48	3.43	5.19	6.54	6.53	6.89	9.11	9.63	10.26	12.70	11.22
t-stat	0.70	1.64	2.50	3.09	3.04	3.17	4.04	4.25	4.51	5.19	6.61
SD	15.70	15.59	15.43	15.75	15.98	16.17	16.80	16.86	16.95	18.22	12.63
Skew	-0.60	-0.65	-0.42	-0.48	-0.51	-0.45	-0.47	-0.21	-0.19	-0.02	1.46
Kurt	2.27	2.18	2.37	1.48	2.32	2.06	2.80	3.32	3.24	3.44	8.40

Panel B: Portfolio Rebalancing takes place on the Seventh Trading Day of Month

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	2.23	4.19	5.83	6.20	6.82	8.19	8.24	10.10	10.09	11.52	9.29
t-stat	1.01	1.86	2.54	2.62	2.87	3.44	3.39	4.10	3.90	4.32	5.27
SD	16.50	16.81	17.06	17.64	17.66	17.73	18.06	18.34	19.25	19.87	13.12
Skew	-0.49	-0.53	-0.26	-0.33	-0.41	0.00	0.17	0.19	0.23	0.21	1.44
Kurt	1.94	2.05	2.28	2.34	1.88	3.28	3.61	3.95	4.74	5.14	10.71

Panel C: Portfolio Rebalancing takes place on the Fourteenth Trading Day of Month

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	2.86	4.45	5.57	6.61	6.86	6.75	7.73	9.65	8.25	10.46	7.60
t-stat	1.38	2.10	2.61	3.00	3.16	2.98	3.44	4.21	3.49	4.48	5.10
SD	15.35	15.76	15.91	16.38	16.19	16.85	16.74	17.05	17.61	17.39	11.10
Skew	-0.84	-0.41	-0.40	-0.44	-0.33	-0.32	-0.46	-0.13	-0.27	-0.18	0.86
Kurt	2.55	1.46	2.10	1.89	1.89	2.24	2.82	2.64	2.58	2.73	5.40

Panel D: Portfolio Rebalancing takes place on the Twenty-First Trading Day of Month

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	HML
Mean	1.36	4.17	4.90	5.75	6.42	8.15	7.93	9.78	10.80	11.87	10.50
t-stat	0.65	1.95	2.24	2.64	2.90	3.57	3.44	4.14	4.42	4.66	5.87
SD	15.70	15.89	16.29	16.21	16.49	16.99	17.14	17.56	18.19	18.95	13.32
Skew	-1.07	-0.84	-0.88	-0.90	-0.65	-0.55	-0.36	-0.23	-0.31	-0.21	1.50
Kurt	3.56	2.89	3.52	3.55	2.85	3.01	2.45	2.16	2.70	4.49	14.71

This table represents mean, t-statistics, standard deviation, skewness, kurtosis of monthly excess returns of portfolio value-weighted returns of a strategy based on the WFL measure, when portfolio rebalancing takes place not in the end of the month as suggested in the main model, but on the first, seventh, fourteenth or twenty-first day in month. Mean and standard deviation are annualized and in percent. The sample period is from January 1963 to December 2018