The Impact of Recency Effects on Stock Market Prices

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Abstract: Experimental evidence shows that recent observations have a stronger impact on the formation of beliefs than observations from the more distant past. Thus, if investors judge upon a stock's attractiveness based on historical return data, they presumably overweight the most recent returns. Based on this simple idea, we propose a new empirical measure of recency adjustment that reflects the ordering of previous returns. Based on the conjectured behavioral mechanisms, recency adjustment should be systematically related to stock mispricing. We use US stock market data from 1926 to 2016 to support this hypothesis empirically and show that recency adjustment is a strong predictor for the cross-section of subsequent returns.

Keywords: Behavioral Finance, Recency Effect, Cross-Section of Stock Returns, Return Predictability

JEL: G02, G12, G14

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1. Introduction

According to the efficient market hypothesis, prices reflect all available information immediately in an unbiased way (Fama, 1970). This null hypothesis of efficient stock markets has been challenged by numerous empirical studies during the last decades (see Harvey et al., 2016 for a review of market anomalies). Various judgment biases have been proposed as behavioral explanations that basically all share a common foundation: either comparably relevant information is underweighted or comparably irrelevant information is overweighted. Referring to the latter case, recent research suggests that mispricing can emerge if investors consider historical return distributions as more representative for future return distributions than they really are (see Barberis et al., 2016). In addition, experimental evidence suggests that individuals tend to overweight recent information. Combining these two arguments, we empirically examine whether recency effects in historical returns systematically influence stock market prices.

One easy accessible – though often meaningless – piece of stock information is its historical return distribution. We argue that investors use this information in order to decide which stocks from their choice set they want to trade. Moreover, cross-sectional narrow-framing implies that investors are interested in the returns of individual stocks rather than their overall portfolio returns. These assumptions are in line with Bali et al. (2011) and Barberis et al. (2016). They argue that investors apply a value function, which reflects skewness preferences and cumulative prospect theory (CPT), on historical returns in order to evaluate a stock's attractiveness. This evaluation process should also be strongly affected by the ordering of previous returns: recent returns are easier to remember than distant return observations. Moreover, the most recent returns are always included in return statistics while returns from the distant past are only considered if the evaluation period is sufficiently long. We therefore hypothesize that recent returns receive a higher weight in the stock evaluation process.

Based on this argument, we introduce the covariance between return and the time that has passed since the return observation as a measure of recency adjustment RA. This proposed measure RA adjusts the time-independent application of value functions for recency effects. RA carries the advantage that it neither depends on the specific form of the value function nor on the specific way recent and distant observations are weighted. The only necessary assumptions we rely on are that investors' value functions are upward-sloping (preference for higher compared to lower historical returns) and that recent observations receive a higher decision weight than distant observations.

For low values of RA, recent returns are comparably high while distant returns are comparably low. If investors judge on a stock's attractiveness mainly based on the most recent observations, they will assign a higher value to such low-RA stocks. The resulting buying pressure might increase the stock price beyond its fundamental value resulting in low subsequent returns. The idea that historical return observations receive different weights in information processing is also put forward by Cosemans and Frehen (2017). They argue that salient observations (that is, days with high absolute market excess returns) influence decisions disproportionally strong. Although the weighting intuition behind RA is similar to the ST-measure proposed by Cosemans and Frehen (2017), we empirically show that RA and ST are unrelated empirically.

One main issue when it comes to empirically testing our line of argument lies in the choice of the time horizon RA should be based on. For example, Bali et al. (2011) consider daily returns of the previous month in order to come up with their skewness proxy MAX while Barberis et al. (2016) use monthly returns of the previous five years to calculate CPT-values. Based on an analysis of the New York Times stock market section, we consider a monthly and an annual horizon in our main analyses as most appropriate. However, we also provide results for additional time horizons in the Online Appendix.

Our empirical analysis of US stocks between 1926 and 2016 strongly supports the theoretical predictions that link recency adjustment to stock mispricing. Examining the predictive power of RA on a monthly basis in decile portfolio sorts, high-RA stocks outperform low-RA stocks by 1.20% in the subsequent month on a value-weighted Fama-French-Carhart-adjusted basis. Fama-MacBeth-regressions show that the return impact of RA is not captured by other known determinants of cross-sectional return predictability. Similarly, if RA is based on returns of the previous year, its predictability is also highly significant both in statistical and economic terms. Supporting a behavioral explanation, the return impact is particularly pronounced among stocks with presumably high limits to arbitrage. Our empirical findings cannot be explained by micro-structure effects, are robust to various methodological specifications, hold in both halves of the sample period, and are valid beyond small and penny stocks.

These empirical findings mainly contribute to two strands of literature. First, we support recent research in the field of behavioral finance arguing that investor behavior is erroneously influenced by historical return distributions. The detected recency bias is shown to have a systematic impact on stock market prices, thereby further challenging the efficient market hypothesis. Second, our work is related to experimental evidence on information ordering effects. We show that recency biases detected in the laboratory do not only influence individual decision making but also real-world stock market prices. We will shortly review these two literature strands in the following chapter before theoretically introducing and empirically testing the implications of recency.

2. Literature Review

2.1. Stock Evaluation based on Past Returns

Barberis et al. (2016) argue that investors use the distribution of past returns as an easily available proxy for the formation of future return expectations. Nolte and Schneider (2018) show that experimental subjects indeed use prior returns to judge on a stock's attractiveness although this information is irrelevant from a normative perspective in their experimental setting. Bali et al. (2011) conjecture that investors use the maximum daily return of the previous month, MAX, to form skewness expectations. On the basis of individuals' skewness preferences, Barberis and Huang (2008) hypothesize that stocks with positively skewed payoff profiles should be overvalued. Bali et al. (2011) empirically support this hypothesis since the relationship between MAX and subsequent returns is significantly negative. More recently, Cosemans and Frehen (2017) argue that investors form return expectations predominantly based on the most salient past returns. They propose a salience measure ST that is significantly related to subsequent returns. Barberis et al. (2016) estimate a cumulative prospect theory value based on previous stock returns which is supposed to reflect the stock's perceived attractiveness. They relate their resulting TK-measure to mispricing and show its ability to forecast cross-sectional return differences. In conclusion, the existing literature provides strong support for the hypothesis that investors' investment decisions depend on the perceived attractiveness of historical return patterns and that this behavior can induce stock mispricing.

However, the existing empirical literature does not explicitly examine whether the ordering of these historical returns is also systematically related to mispricing. Barberis et al. (2016) calculate a TK-measure which overweights recent returns as a robustness test. Cosemans and Frehen (2017) calculate their salience measure based on different horizons and argue that the predictive power should decrease in the formation period length as distant observations receive lower weight. However, both papers do not separately evaluate the role of recency or return ordering effects for subsequent stock returns.

2.2. Influence of Recency Effects on Decision Making

Many researchers have experimentally examined whether the ordering of information influences beliefs and decision making (see for example evidence in Murdock, 1962; Anderson, 1965; Stewart, 1965; Slovic and Lichtenstein, 1971). These early psychological studies present evidence for both primacy effects (early information is overweighted) and recency effects (recent information is overweighted). Hogarth and Einhorn (1992) reconcile these findings with experimental support for their belief-adjustment model: On the one hand, primacy effects occur if simple data is processed and subjects state their beliefs only after they observe an entire sequence. On the other hand, recency effects are prevalent in the processing of complex information and a step-by-step updating of beliefs. Based on this model, Tuttle et al. (1997) expect recency effects to be dominant in a financial market setting. In their experimental market environment, recent information was indeed more influential than earlier information. This bias also substantially affected laboratory market prices such that market trading mechanisms seem unable to eliminate the judgment biases associated with ordering effects.

Since individuals seem to consider small and recent samples as more representative for distributions than they really are (Tversky and Kahneman, 1974), various models have been proposed that transfer the experimental findings to a financial market setting. For example, Afik and Lahav (2015) use experimental data to calibrate their model of price belief formation based on historical price patterns. Barberis et al. (2015) propose an X-CAPM that builds on the assumption that some investors over-extrapolate recent price changes in their belief formation. Collin-Dufresne et al. (2017) model young agents to underweight distant events they have not personally experienced. Barberis et al. (2018) present a model which explains the occurrence of aggregate market price bubbles with investors who weight recent stock market returns stronger than distant returns in their stock purchasing decisions.

Greenwood and Shleifer (2014) empirically examine the role of past market returns for the formation of return expectations using US survey data. Accordingly, market return expectations are substantially influenced by recent preceding market returns. More specifically, they show that returns of the most recent quarter are ten times stronger reflected in return expectations compared to returns that were realized four quarters previously. Adam et al. (2017) empirically support the notion of biased expectation formation with respect to market returns. They set up a model environment where investor optimism is driven by recent returns such that these investors might increase aggregate market prices beyond fundamental values.

The importance of prior returns for investor behavior is also well-established in the mutual fund literature. For instance, investors showing more behavioral biases tend to buy funds with high recent returns according to Bailey et al. (2011). Barber et al. (2016) show that fund flows are especially driven by recent fund returns compared to fund returns from the more distant past which shows mutual fund investors' propensity to rely on the most recent evidence. More specifically, the impact of the most recent monthly return is more than twice as high than the five-months-ago return. While this use of past fund returns as a representation for future fund returns might be reasonable if fund returns are persistent (Grinblatt and Titman, 1992), we conjecture that investors behave similarly with respect to individual stock trading.

Turning to the cross-section of expected stock returns, empirical evidence on the relevance of recency is comparably rare thus far. Profits from short-term reversal (REV) strategies might be interpreted as indicative evidence that investors overreact with respect to the most recent news and returns (see for example Jegadeesh and Titman, 1995). However, REV does not explicitly trade off recent versus distant return observations. Moreover, returns associated with REV are often attributed to bid-ask-bounce effects or stock illiquidity (Conrad et al., 1997 and Avramov et al., 2006). We empirically show, that our measure of recency adjustment remains relevant beyond these effects and after controlling for REV. Bhootra and Hur (2013) empirically consider recency effects more directly: They show that the predictive power associated with a stock's nearness to its 52-week high (George and Hwang, 2004) depends on the timing of the 52-week high. Bhootra and Hur (2013) find that the 52-week high serves as a stronger anchor if it was realized in the recent past. Although their proposed recency ratio RR applies to the 52-week high and not to the ordering of return observations in general, their empirical analyses strongly support our conjecture that recency effects play a role in investors' belief formation. Our empirical analyses also control for the predictive power associated with RR.

3. Recency Effects in Financial Markets

3.1. Introduction of Recency Adjustment

In this chapter, we incorporate recency effects into the judgment of investors in order to understand how the ordering of returns can lead to over- or undervaluation. Based on the presented literature, we assume that investors judge upon a stock's attractiveness based on realized returns of the previous D trading days. Investors evaluate these returns r using a value function $v(r)$. In line with the experimental findings, the weight w for each return observation depends on the time d that has passed since its occurrence. In this setting, the recency-adjusted value $RAV_{i,t}$, which reflects the perceived attractiveness of a stock i at time t, is given as

$$RAV_{i,t} = \frac{1}{D} \sum_{d=1}^{D} v(r_{i,t+1-d}) w(d). \tag{1}$$

We do not confine our analysis to explicit functions $v(r)$ and $w(d)$ such that our line of argument does not depend on specific assumptions how exactly investors evaluate returns and trade off recent versus distant observations.[1] We merely restrict $v(r)$ to be increasing in r since all investors should favor higher returns over lower returns. With respect to $w(d)$, we only assume that distant observations are underweighted compared to recent observations following experimental evidence. These considerations imply

$$\frac{\partial v}{\partial r} > 0 \quad \text{and} \quad \frac{\partial w}{\partial d} < 0. \tag{2}$$

[1] This implies that Equation (1) can also be considered as a general version of Equation (9) in Barberis et al. (2016). In their analysis, Barberis et al. (2016) state that $w(d)$ is an exponential function and that $v(r)$ reflects preferences according to cumulative prospect theory. However, Tversky and Kahneman (1992) and Zeisberger et al. (2012) show that CPT-preferences are different both between individuals and across time. Moreover, there might also be investors whose evaluation is not well described by CPT.

Equation (1) can be restated as

$$
\begin{aligned}
RAV_{i,t} &= E_{t,d\in[1,D]}[v(r_{i,t+1-d})w(d)] \\
RAV_{i,t} &= E_{t,d\in[1,D]}[v(r_{i,t+1-d})]E_{t,d\in[1,D]}[w(d)] + Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)] \qquad (3)
\end{aligned}
$$

where $E_{t,d\in[1,D]}[\cdot]$ and $Cov_{t,d\in[1,D]}[\cdot]$ denote the expected value and the covariance at time t based on the previous D trading days, respectively. Equation (3) allows to differentiate between the influence of return evaluation via $v(r)$ and the influence of recency effects. The first part of the sum simply reflects the impact of the value function $v(r)$ since $E_{t,d\in[1,D]}[w(d)]$ does not depend on i and t. The previous literature largely focuses on this part of the equation in order to explain how investors assess stocks based on prior returns. A recent exception is provided by Cosemans and Frehen (2017) who also argue that a covariance term including w influences a stock's perceived attractiveness. However, they assume that w depends on the individual returns' salience (that is $w(r_{i,t+1-d})$) while w is exclusively influenced by the timing of returns in our setting.[2]

Under the assumption that the functions $v(r)$ and $w(d)$ are real analytic, they can be restated as an infinite order Taylor series expansion around a_v and a_w, respectively:

$$
v(r_{i,t+1-d}) = \sum_{k=0}^{\infty} \frac{\left.\frac{\partial^k v}{\partial r^k}\right|_{r=a_v}}{k!} \, (r_{i,t+1-d} - a_v)^k, \qquad (4)
$$

$$
w(d) = \sum_{k=0}^{\infty} \frac{\left.\frac{\partial^k w}{\partial d^k}\right|_{d=a_w}}{k!} \, (d - a_w)^k. \qquad (5)
$$

Using these specifications we can rewrite the covariance term from Equation (3) as

$$
\begin{aligned}
Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)] &= \left.\frac{\partial v}{\partial r}\right|_{r=a_v} \left.\frac{\partial w}{\partial d}\right|_{d=a_w} Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d] \\
&+ \left.\frac{\partial v}{\partial r}\right|_{r=a_v} \sum_{k=2}^{\infty} \frac{\left.\frac{\partial^k w}{\partial d^k}\right|_{d=a_w}}{k!} \, Cov_{t,d\in[1,D]}[r_{i,t+1-d}, (d - a_w)^k] \\
&+ \left.\frac{\partial w}{\partial d}\right|_{d=a_w} \sum_{k=2}^{\infty} \frac{\left.\frac{\partial^k v}{\partial r^k}\right|_{r=a_v}}{k!} \, Cov_{t,d\in[1,D]}[(r_{i,t+1-d} - a_v)^k, d]
\end{aligned}
$$

[2] Strictly speaking, Cosemans and Frehen (2017) consider salience to be driven by absolute market excess returns. However, Chapter 4.3 shows that our analyses are not affected by the specific choice of a reference return.

$$+\sum_{k=2}^{\infty}\sum_{j=2}^{\infty}\frac{\left.\frac{\partial^k v}{\partial r^k}\right|_{r=a_v}}{k!}\frac{\left.\frac{\partial^j w}{\partial d^j}\right|_{d=a_w}}{j!}\quad Cov_{t,d\in[1,D]}[(r_{i,t+1-d}-a_v)^k,(d-a_w)^j]. \tag{6}$$

Considering Equations (2) and (3), the first row directly implies that the covariance between returns and past time, $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$, negatively influences $RAV_{i,t}$ for all $a_v, a_w \in \mathbb{R}$ since the value function is upward sloping and distant returns receive lower weight. The other three parts of Equation (6) show the higher moment impact of $v(r)$ and $w(d)$. Since we do not restrict our analysis to specific functional forms for $v(r)$ and $w(d)$, the level of these higher order derivatives is highly ambiguous such that we have no clear hypothesis on the directional impact of the corresponding covariance terms. As a consequence, our subsequent analyses focus on the first part of Equation (6) which allows for unambiguous predictions how recency effects influence stock market prices.[3]

Equation (6) implies that the recency adjustment

$$RA_{i,t} \equiv Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d] \tag{7}$$

lowers the stock's perceived attractiveness since high values of $RA_{i,t}$ imply that high returns date back to the distant future while recent returns tend to be low. Hence, high values of $RA_{i,t}$ should trigger an undervaluation while low values speak in favor of an overvaluation. We therefore hypothesize that $RA_{i,t}$ and subsequent returns should be positively related. We test this theoretical conjecture in the following empirical analysis.

3.2. Choice of Formation Period

Before implementing $RA_{i,t}$ empirically, one question warrants further discussion: which formation period should be used in order to estimate $RA_{i,t}$, that is, which value D should be chosen in Equation (7)? The above-mentioned literature applies very different approaches: Barberis et al. (2016) choose a five-year formation period which is the average time frame

[3]Note that the concept of recency adjustment is naturally applicable to explicit functions $v(r)$ and $w(d)$ as well. While such an approach involves a loss of generality, it would allow for precise estimates of $Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)]$ including the potential impact of higher moments. While our main analyses examine the general case in order to avoid potentially doubtful assumptions, we also investigate the specific case of a prospect theory value function and an exponential weighting function in the Online Appendix. Across different specifications, the correlation between $Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)]$ and $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$ ranges from 0.90 to 0.94 in absolute terms. This indicates that $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$ captures large proportions of the conjectured recency effects empirically since higher order moments seem to play only a minor role in the examined cases.

covered by stock charts presented in investment handbooks. Bali et al. (2011) and Cosemans and Frehen (2017) use daily returns of the previous month in order to estimate their measures of MAX and ST, respectively. This is in line with recent evidence by Gargano and Rossi (2018) who show that discount broker customers log into their online accounts once every 28 days on average. Cosemans and Frehen (2017) point out that the behavioral assumption that investors suffer from cognitive limitations speaks in favor of a short horizon, too. Moreover, they argue that this choice is consistent with the commonly applied monthly horizon for the measurement of subsequent returns.

Benartzi and Thaler (1995) argue that one year is the most plausible horizon over which investors aggregate portfolio returns given that they receive reports from their mutual funds, about their retirement savings, or about company earnings often on an annual basis. Benartzi and Thaler (1995) also show that an annual evaluation period fits the magnitude of the equity premium in their model of investors with myopic loss aversion (see for example same time period in the model of Barberis et al., 2001). Thus, one year might be a reasonable time span for the evaluation of previous returns in our setting as well. However, investors also receive stock return information with a higher frequency, for example through interim financial reporting, frequent trading in the stock market, or daily newspaper articles. Referring to the latter, we analyzed the return horizons commonly reported in the stock market section of the New York Times beginning in 1931. In most years, the New York Times presented 3-month charts for stock market indices. For individual stocks, daily returns, 52-week high, 52-week low, and year-to-date-returns are often provided while longer time horizons are hardly ever considered.

Of course, other return time frames are available to investors. This holds especially true for the internet era in the last few decades of our sample period. However, we expect that investors will often use the information that is most easily available for them which indicates a formation period of at most one year. Within this time span, the return evaluation periods are presumably heterogeneous for different stocks and investors. In the market aggregate, this heterogeneity implies that recent returns receive high weight (since they are included in all possible evaluation periods) while distant returns receive lower weight (since they are only considered if the evaluation period is sufficiently long). Beside the psychologically driven recency bias (see Section 2.2), this aggregation mechanisms can thus additionally constitute to the overweighting of recent observations. Although the exact choice of D

remains arbitrary to some degree, we think that the outlined arguments are best reflected by choosing one month and twelve months as the two main specifications for D. However, we also provide results for time horizons of 6, 36, and 60 months in the Online Appendix. As one would expect, the conjectured return predictability associated with recency adjustment becomes smaller for longer formation periods, but even for $D = 60$ months it remains significant at 10% in Fama-MacBeth-regressions.

4. Empirical Analyses

4.1. Data and Variable Construction

Data Sources. Our analyses include common ordinary US shares traded on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ between 1926 and 2016. Stock market data are sourced from the Center for Research in Security Prices (CRSP). In order to calculate risk-adjusted returns and idiosyncratic volatility, we obtain monthly and daily Fama-French-Carhart (FFC) factors and risk-free rate data from Kenneth R. French's homepage.[4] Accounting data comes from COMPUSTAT.[5] Since COMPUSTAT does not provide book equity data for the beginning of our sample period, we also use book equity data from Kenneth R. French's homepage in addition.

Recency Adjustment. Our main variable, the recency adjustment $\mathrm{RA_M}$ as introduced in Chapter 3, is calculated based on daily returns of the previous month. It is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. In addition, we also use $\mathrm{RA_A}$ in our empirical test, which reflects the return ordering of the previous twelve months. It is computed as the covariance between monthly returns and the corresponding number of months until the end of the formation period.

Control Variables. The market value of a stock's equity, MV, is calculated as number of shares outstanding times stock price at the end of month. In order to control for long-term reversal, momentum, and short-term reversal effects, we compute ltREV, MOM, and REV as the returns of months $t-60$ to $t-13$, $t-12$ to $t-2$, and $t-1$, respectively. Idiosyncratic return volatility, IVOL, is estimated as the annulazied volatility of residuals from a regression of

[4]See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[5]Both CRSP and COMPUSTAT data were accessed via Wharton Research Data Services (WRDS). For additional robustness tests, we also use Optionmetrics data from WRDS in the Online Appendix.

daily stock returns on the Fama-French-factors in the previous month (Ang et al., 2006b). Further, we apply the Amihud (2002) illiquidity measure, ILLIQ. It is calculated as the ratio of absolute daily return and daily dollar trading volume averaged over the previous year. The market beta, BETA, is estimated using daily returns of the previous year. The book value of equity is calculated in accordance with Fama and French (1993), that is, we use annual balance sheet data at the earliest at the end of June of the following year and firms with negative book values are excluded from our sample. The book-to-market-ratio BM is then calculated as book value of equity divided by the most recent market value of equity.

In order to capture return skewness effects, we include the maximum and minimum daily returns of the previous month (MAX and MIN) as proposed by Bali et al. (2011). Since Barberis et al. (2016) argue that investors assess a stock's attractiveness based on cumulative prospect theory preferences, we include their TK-measure as a control variable. It is estimated using monthly market excess returns over the previous five years. In addition, Cosemans and Frehen (2017) argue that investors overweight salient returns which is why we incorporate their salience theory measure, ST, estimated using daily returns of the previous month. Finally, we control for the recency ratio, RR, as introduced by Bhootra and Hur (2013). RR is calculated as one minus the number of days since the 52-week high over 364, that is, RR is standardized between 0 and 1 where a higher value of RR shows that the 52-week high was realized in the more recent past.

Sample Size. An observation is included in our sample, if all variables described above are available. This procedure results in 1,789,306 monthly observations. Our sample period starts in January 1931, since we need five years of return history to estimate ltREV and TK, and ends in December 2016.

Summary Statistics. Pooled sample summary statistics and correlation coefficients for all the introduced variables are provided in Table 1. Notably, our new measure of monthly recency adjustment RA_M shows very little correlation with all the other variables indicating rather unique information content. As expected, RA_A shows substantial negative (positive) correlation with short-term reversal (momentum) since RA_A reflects the timing of monthly returns in the previous year by construction. Similar arguments apply for its negative correlation with MAX, MIN, and ST: MAX and MIN also reflect recent stock returns; the same holds true for ST since it is strongly correlated with REV. Finally, the only modest negative correlation with the recency ratio RR shows that our measure of recency adjustment substantially differs from the recency of the 52-week high.

Table 1. Summary Statistics
This table reports pooled sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients for the main variables of the analyses on a monthly basis. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. MV is the market value of equity. BM denotes the book-to-market ratio. MOM, ltREV, and REV are the returns of months $t-12$ to $t-2$, $t-60$ to $t-13$, and $t-1$, respectively. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX and MIN denote the maximum and minimum daily return of the previous month, respectively. Amihud (2002) illiquidity measure, ILLIQ, and market beta, BETA, are estimated over the previous year. RR is the recency ratio as introduced by Bhootra and Hur (2013). TK denotes the TK-value as proposed by Barberis et al. (2016). ST reflects the salience theory value of Cosemans and Frehen (2017). ILLIQ is stated in million; RA_M, RA_A, ltREV, REV, MAX, MIN, and ST are stated in %. The sample period is from January 1931 to December 2016.

	RA_M	RA_A	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
mean	-0.00	0.07	0.85	18.93	1.05	14.81	82.01	1.28	0.38	6.56	-5.36	5.25	0.55	-0.06	0.59
SD	4.68	15.83	0.61	2.18	3.09	62.62	211.28	14.98	0.36	7.76	4.75	49.67	0.35	0.04	3.08
$q_{0.1}$	-4.44	-15.76	0.15	16.20	0.20	-37.93	-56.62	-12.67	0.13	1.90	-10.40	0.00	0.03	-0.11	-1.98
$q_{0.5}$	0.03	0.10	0.80	18.81	0.67	7.56	38.82	0.36	0.28	4.57	-4.00	0.14	0.59	-0.05	0.29
$q_{0.9}$	4.36	16.02	1.64	21.83	1.83	66.34	235.97	15.08	0.72	12.62	-1.71	6.57	0.98	-0.02	3.32

Correlation coefficients															
RA_M	1.00														
RA_A	-0.03	1.00													
BETA	0.01	0.05	1.00												
ln(MV)	-0.01	-0.02	0.21	1.00											
BM	0.02	0.02	0.01	-0.19	1.00										
MOM	-0.00	0.14	0.06	0.09	-0.10	1.00									
ltREV	-0.01	0.00	0.13	0.13	-0.08	-0.04	1.00								
REV	0.06	-0.46	-0.01	0.04	-0.05	-0.00	-0.02	1.00							
IVOL	-0.02	-0.04	-0.06	-0.39	0.18	-0.10	-0.08	0.13	1.00						
MAX	-0.01	-0.12	0.00	-0.28	0.14	-0.09	-0.06	0.30	0.90	1.00					
MIN	0.04	-0.12	-0.02	0.33	-0.18	0.08	0.05	0.22	-0.80	-0.59	1.00				
ILLIQ	0.01	-0.04	-0.06	-0.17	0.21	-0.02	-0.05	0.02	0.26	0.21	-0.21	1.00			
RR	0.03	-0.06	-0.02	0.21	-0.11	0.49	-0.02	0.12	-0.20	-0.13	0.22	-0.04	1.00		
TK	0.00	-0.02	0.09	0.28	-0.17	0.26	0.42	0.10	-0.38	-0.27	0.38	-0.09	0.30	1.00	
ST	0.01	-0.25	0.00	-0.11	0.04	-0.04	-0.03	0.56	0.52	0.71	-0.05	0.14	0.00	-0.06	1.00

4.2. Cross-Sectional Implications of the Monthly Recency Adjustment

We now test our main prediction with respect to the effect of recency. Distant returns should receive lower weight when investors judge upon a stock's attractiveness compared to recent returns. In line with this argument, Chapter 3 implies that our measure of recency adjustment should be positively related with subsequent stock returns. Given the large strand of literature arguing that the return distribution of the previous month is relevant for investors' return expectations (see for example Bali et al., 2011 and Cosemans and Frehen, 2017), we first investigate the predictive power of our monthly measure RA_M.

Portfolio Sorts. The portfolio sorts in Table 2 show the univariate relationship between RA_M and subsequent returns. At the end of each month, the stocks in our sample are sorted into decile portfolios based on RA_M. Table 2 provides subsequent returns R and FFC-adjusted returns α_{FFC} for both equally- and value-weighted portfolios. Accordingly, the top-RA_M decile outperforms the bottom decile by 2.15% per month on an equally-weighted basis. This return spread is highly significant (t-statistic of 12.60) and not subsumed by the Fama-French-Carhart risk factors. According to Panel B of Table 2, the subsequent return impact of RA_M is substantially smaller if portfolio returns are computed on a value-weighted basis. However, the return spread of 1.30% is still highly significant. The annualized return premium of 16.77% is economically relevant as well. Thus, the evidence from Table 2 strongly supports our central hypothesis. Low levels of RA_M seem to increase the perceived stock attractiveness since recent returns are high compared to more distant returns. As a consequence, these stocks become overvalued such that their subsequent returns are low.

Table 2. Portfolio Sorts based on Monthly Recency Adjustment
This table reports monthly decile portfolio sorts based on monthly recency adjustment, RA_M, for the sample period from January 1931 to December 2016. RA_M is based on the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. The table presents portfolio averages for RA_M and subsequent monthly returns R. The FFC-adjusted portfolio returns α_{FFC} and the corresponding factor loadings are also provided. Panel A is based on equally-weighted portfolios while Panel B applies value-weighting. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns and alphas are stated in %.

	Panel A: equally-weighted portfolios							Panel B: value-weighted portfolios						
	RA_M	R	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	RA_M	R	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}
low	-6.09	0.10	-1.16	1.07	0.97	0.35	-0.24	-5.04	0.23	-0.86	1.13	0.27	0.06	-0.07
2	-2.70	0.93	-0.24	1.03	0.65	0.27	-0.16	-2.64	0.72	-0.26	1.00	0.14	0.12	-0.08
3	-1.57	1.18	0.01	1.01	0.59	0.34	-0.15	-1.55	0.83	-0.16	0.99	0.02	0.12	-0.02
4	-0.80	1.23	0.12	0.97	0.45	0.27	-0.11	-0.80	0.92	-0.01	0.95	-0.06	0.06	0.01
5	-0.16	1.36	0.26	0.98	0.45	0.27	-0.12	-0.16	1.06	0.14	0.96	-0.09	0.09	-0.03
6	0.45	1.29	0.17	0.99	0.41	0.26	-0.08	0.45	0.98	0.04	0.99	-0.11	0.10	-0.03
7	1.10	1.46	0.29	1.03	0.42	0.32	-0.08	1.10	1.06	0.07	1.05	-0.13	0.08	0.02
8	1.88	1.54	0.35	1.10	0.44	0.26	-0.10	1.87	1.17	0.18	1.11	-0.11	0.06	-0.05
9	3.02	1.79	0.50	1.17	0.59	0.26	-0.08	2.96	1.21	0.16	1.16	-0.05	0.09	-0.04
high	6.53	2.25	0.95	1.17	0.92	0.28	-0.22	5.39	1.53	0.33	1.27	0.20	0.16	-0.09
10-1	12.61	2.15	2.12	0.10	-0.05	-0.06	0.02	10.43	1.30	1.20	0.14	-0.07	0.10	-0.02
t(10-1)		(12.60)	(11.81)	(1.55)	(-0.50)	(-0.90)	(0.27)		(6.75)	(6.29)	(2.06)	(-0.59)	(0.94)	(-0.24)

In Chapter 3, we argue that RA adjusts the time-independent application of value functions for recency effects. This implies that RA should be particularly relevant even after controlling for variables that reflect the time-independent attractiveness of historical return patterns. We therefore conduct ten times ten conditional double sorting first on each of the variables from Table 1 and second on RA_M. The resulting portfolios are then aggregated across the control variables. The resulting decile portfolio returns are provided in Appendix Table 8. After taking the controls into account, the monthly FFC-adjusted value-weighted return spreads still range from 1.18% to 1.79%.[6] Thus, the return pattern associated with RA_M is not captured by one of these variables. In particular, it remains significant after controlling for those measures that have been introduced previously to reflect the perceived attractiveness of historical returns.

Fama-MacBeth-Regressions. In this subsection, we conduct regression analyses following Fama and MacBeth (1973) in order to jointly control for other known determinants of cross-sectional return differences. The corresponding regression estimates are provided in Table 3. The coefficients for RA_M are highly significant in all specifications. The magnitude even slightly increases if control variables are considered as additional explanatory variables. Further, the effect is not subsumed by IVOL, REV, MAX, MIN, and TK which are also associated with investors' preferences for specific historical return patterns. The reason is that these variables are linked to the value function of investors (first part of Equation (3)) while RA_M adjusts these measures for return ordering effects (second part of Equation (3)).[7]

4.3. Cross-Sectional Implications of the Annual Recency Adjustment

Based on the arguments of Benartzi and Thaler (1995) and our considerations in Chapter 3.2, we also examine the annual recency adjustment RA_A in the following empirical tests.

[6]In our Online Appendix, we also provide qualitatively similar results for equally-weighted and raw returns. In addition, we present average portfolio characteristics for each decile.

[7]The findings remain qualitatively the same if further corresponding control variables are included in the regression analyses. Our Online Appendix shows that the consideration of downside beta (Ang et al., 2006a), return skewness, idiosyncratic return skewness, and return coskewness (Harvey and Siddique, 2000) does not influence the magnitude of RA_M-coefficients. The same holds true if TK is calculated using daily returns of the previous month instead of monthly returns of the previous five years. Moreover, the Online Appendix also shows that the impact of RA_M remains robust in all specifications if value-weighted Fama-MacBeth-regressions are applied. We can also rule out that the findings are driven by some extreme values of the explanatory variables since the results remain qualitatively the same if all explanatory variables are winsorized at 1% and 99%.

Table 3. Monthly Recency Adjustment in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.2843	3.6506	3.4646	3.2557	3.7959	3.6385	3.5292	3.2400	3.1194
	(6.06)	(4.43)	(4.71)	(4.14)	(5.84)	(5.62)	(5.51)	(5.22)	(5.00)
RA_M	0.1585	0.1765	0.1850	0.1898	0.1948	0.1933	0.1924	0.1931	0.1930
	(19.05)	(21.62)	(22.25)	(22.89)	(23.44)	(23.57)	(23.54)	(23.47)	(23.58)
BETA		-0.0109	-0.0628	-0.0827	-0.0024	0.0242	0.0417	0.0185	0.0280
		(-0.09)	(-0.59)	(-0.73)	(-0.02)	(0.22)	(0.38)	(0.18)	(0.27)
ln(MV)		-0.1377	-0.1383	-0.1222	-0.1421	-0.1332	-0.1441	-0.1352	-0.1314
		(-3.37)	(-3.82)	(-3.17)	(-4.43)	(-4.21)	(-4.67)	(-4.55)	(-4.46)
BM		0.0734	0.1245	0.0793	0.0820	0.0767	0.0799	0.0770	0.0760
		(2.43)	(4.35)	(2.96)	(3.14)	(2.97)	(3.13)	(2.93)	(2.91)
MOM			0.0079	0.0075	0.0077	0.0079	0.0052	0.0063	0.0063
			(4.14)	(3.75)	(3.92)	(4.01)	(2.51)	(3.26)	(3.32)
ltREV			-0.0008	-0.0010	-0.0010	-0.0010	-0.0009	-0.0005	-0.0005
			(-2.37)	(-2.64)	(-2.81)	(-2.74)	(-2.71)	(-1.52)	(-1.37)
REV				-0.0663	-0.0710	-0.0703	-0.0720	-0.0717	-0.0670
				(-16.63)	(-17.30)	(-17.22)	(-17.65)	(-17.46)	(-15.75)
IVOL					0.2865	-0.0569	-0.0042	-0.0070	0.1701
					(0.79)	(-0.16)	(-0.01)	(-0.02)	(0.48)
MAX					-0.0172	-0.0128	-0.0143	-0.0145	0.0071
					(-1.40)	(-1.06)	(-1.18)	(-1.22)	(0.56)
MIN					0.0616	0.0570	0.0592	0.0617	0.0919
					(5.19)	(4.89)	(5.12)	(5.37)	(7.14)
ILLIQ						0.0209	0.0208	0.0209	0.0204
						(3.20)	(3.16)	(3.18)	(3.15)
RR							0.6343	0.6267	0.6323
							(6.69)	(6.78)	(6.71)
TK								-3.2942	-3.4459
								(-2.12)	(-2.20)
ST									-0.0732
									(-4.92)

Similarly to RA_M, we expect that low values of RA_A trigger an overvaluation because of comparably attractive recent returns. Thus, RA_A should also be positively related to subsequent returns.

Portfolio Sorts. Again, we first evaluate this hypothesis by the use of portfolio sorts. Table 4 reports subsequent decile portfolio returns. The monthly equally-weighted return spread is 1.82% for raw returns and 1.88% for FFC-adjusted returns. On a value-weighted basis, the return spreads are 1.10% and 1.19%, respectively. Thus, in line with our hypothesis, the annual recency adjustment RA_A is associated with substantial subsequent return spreads. Appendix Table 8 shows that these effects cannot be subsumed by one of the control variables introduced in Table 1 in conditional double sorts. Across all specifications, the value-weighted FFC-adjusted decile return spread amounts to at least 0.88%.[8]

Table 4. Portfolio Sorts based on Annual Recency Adjustment
This table reports monthly decile portfolio sorts based on annual recency adjustment, RA_A, for the sample period from January 1931 to December 2016. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The table presents portfolio averages for RA_A and subsequent monthly returns R. The FFC-adjusted portfolio returns α_{FFC} and the corresponding factor loadings are also provided. Panel A is based on equally-weighted portfolios while Panel B applies value-weighting. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns and alphas are stated in %.

	Panel A: equally-weighted portfolios							Panel B: value-weighted portfolios						
	RA_A	R	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	RA_A	R	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}
low	-20.35	0.47	-0.87	1.07	0.91	0.31	-0.06	-17.51	0.55	-0.63	1.13	0.25	0.16	0.01
2	-9.76	0.83	-0.37	1.05	0.51	0.34	-0.12	-9.58	0.68	-0.34	1.04	0.02	0.16	-0.04
3	-5.99	1.03	-0.18	1.02	0.50	0.36	-0.08	-5.95	0.76	-0.27	1.01	-0.03	0.19	0.01
4	-3.33	1.19	0.04	1.00	0.44	0.36	-0.12	-3.31	0.96	-0.07	1.02	-0.11	0.18	0.03
5	-1.08	1.21	0.09	0.95	0.46	0.30	-0.08	-1.08	0.90	-0.07	0.97	-0.09	0.14	0.01
6	1.06	1.32	0.19	0.99	0.48	0.35	-0.15	1.05	1.08	0.15	0.96	-0.09	0.07	-0.00
7	3.31	1.46	0.31	1.04	0.46	0.27	-0.10	3.29	1.19	0.23	1.02	-0.05	0.10	-0.04
8	5.99	1.57	0.45	1.05	0.53	0.20	-0.15	5.94	1.28	0.32	1.04	0.02	0.02	-0.05
9	9.80	1.76	0.59	1.11	0.63	0.19	-0.18	9.63	1.46	0.42	1.18	0.07	-0.03	-0.05
high	20.45	2.28	1.01	1.23	0.97	0.20	-0.29	17.46	1.65	0.56	1.29	0.37	-0.14	-0.16
10-1	40.80	1.82	1.88	0.15	0.06	-0.12	-0.23	34.96	1.10	1.19	0.15	0.12	-0.30	-0.17
t(10-1)		(9.04)	(8.84)	(3.22)	(0.37)	(-0.91)	(-1.93)		(5.73)	(6.00)	(2.69)	(0.70)	(-2.78)	(-1.82)

Fama-MacBeth-Regressions. Table 5 tests the predictive power of RA_A in Fama-MacBeth-regressions. Although RA_A shows substantial correlation with some of the control variables in Table 1, the impact of RA_A remains significantly positive in all regression specifications. In conclusion, Table 5 supports the conjecture that recency adjustment affects the perceived attractiveness of a stock and is therefore systematically able to predict subsequent returns.[9] Moreover, this chapter demonstrates the relevance of recency adjustment beyond the monthly formation period examined in the previous chapter. Given that many empirical outcomes crucially depend on the chosen formation period (consider for example momentum versus reversal), this serves as an additional indicator for the overarching robustness of the underlying behavioral mechanisms.

[8] Our Online Appendix shows that this also holds true for equally-weighted and raw portfolio returns.

[9] Again, our Online Appendix shows that these findings are robust to the additional consideration of skewness control variables, also hold in value-weighted Fama-MacBeth-regressions, and are not driven by extreme values of the explanatory variables.

Table 5. Annual Recency Adjustment in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.1961	3.3816	3.1822	3.0844	3.7597	3.5895	3.4287	3.1190	3.0098
	(5.10)	(3.90)	(4.06)	(3.84)	(5.86)	(5.61)	(5.46)	(5.10)	(4.90)
RA_A	0.0445	0.0430	0.0401	0.0109	0.0090	0.0094	0.0117	0.0120	0.0120
	(9.49)	(12.08)	(11.16)	(3.49)	(3.03)	(3.17)	(3.90)	(3.98)	(3.96)
BETA		-0.0603	-0.1204	-0.0927	-0.0107	0.0147	0.0350	0.0130	0.0235
		(-0.47)	(-1.03)	(-0.79)	(-0.09)	(0.13)	(0.31)	(0.12)	(0.21)
ln(MV)		-0.1228	-0.1217	-0.1142	-0.1405	-0.1310	-0.1445	-0.1349	-0.1315
		(-2.87)	(-3.15)	(-2.91)	(-4.42)	(-4.18)	(-4.71)	(-4.55)	(-4.49)
BM		0.0685	0.1120	0.0804	0.0844	0.0792	0.0832	0.0807	0.0798
		(2.21)	(3.95)	(2.98)	(3.20)	(3.04)	(3.24)	(3.05)	(3.04)
MOM			0.0062	0.0068	0.0068	0.0069	0.0037	0.0047	0.0048
			(3.20)	(3.31)	(3.34)	(3.36)	(1.68)	(2.28)	(2.34)
ltREV			-0.0008	-0.0009	-0.0009	-0.0009	-0.0009	-0.0004	-0.0004
			(-2.31)	(-2.49)	(-2.59)	(-2.51)	(-2.48)	(-1.16)	(-1.04)
REV				-0.0616	-0.0662	-0.0654	-0.0668	-0.0662	-0.0621
				(-15.82)	(-16.32)	(-16.17)	(-16.66)	(-16.70)	(-14.68)
IVOL					-0.0378	-0.3779	-0.3007	-0.3044	-0.1471
					(-0.10)	(-1.04)	(-0.83)	(-0.86)	(-0.41)
MAX					-0.0119	-0.0077	-0.0092	-0.0094	0.0090
					(-0.99)	(-0.64)	(-0.77)	(-0.79)	(0.72)
MIN					0.0467	0.0418	0.0447	0.0473	0.0737
					(3.88)	(3.54)	(3.81)	(4.08)	(5.60)
ILLIQ						0.0203	0.0202	0.0203	0.0200
						(3.11)	(3.09)	(3.12)	(3.10)
RR							0.7825	0.7787	0.7831
							(8.47)	(8.61)	(8.53)
TK								-3.4887	-3.6089
								(-2.22)	(-2.29)
ST									-0.0646
									(-4.17)

4.4. Further Analyses and Robustness Tests

Support for the Behavioral Line of Argument. Theoretical research points out that behavioral biases should have a more pronounced impact on stock market prices if limits to arbitrage are strong (see De Long et al., 1990 and Shleifer and Vishny, 1997 among others). Based on this idea, empirical analyses provide evidence that stock market anomalies tend to be stronger among stocks of low liquidity (see for example Sadka and Scherbina, 2007, Chordia et al., 2008, and Stambaugh et al., 2015). Consequently, we expect the return patterns associated with RA_M and RA_A to be stronger if limits to arbitrage are more severe.

Initial support for this hypothesis is provided by our portfolio sorts in Tables 2 and 4. In comparison to value-weighted portfolios, the return predictability is stronger for equally-weighted portfolios where small firms receive higher weight. Given that limits to arbitrage are presumably stronger for these smaller firms, the higher effect magnitude is in line with a behavioral line of argument.

Further supporting evidence is provided in Table 6 which presents conditional double sorts. First, each stock is allocated to one portfolio based on a limits to arbitrage proxy. We choose Amihud (2002) illiquidity ILLIQ, idiosyncratic volatility IVOL, and the maximum absolute return of the previous month MAX(|ret|) as proxies since they are both frequently applied in empirical research and available for the entire sample period (Cosemans and Frehen, 2017). Second, we form decile portfolios based on $\mathrm{RA_M}$ and $\mathrm{RA_A}$. Table 6 reports value-weighted FFC-adjusted returns, while our Online Appendix shows that the findings are qualitatively the same for equally-weighted and/or unadjusted returns.

Referring to Panel A of Table 6, the return impact of $\mathrm{RA_M}$ is three to five times larger for the quartile that contains the stocks with the highest limits to arbitrage. For example, the monthly return spread is 3.36% for the quartile of high-ILLIQ stocks while it is only 0.67% for the quartile of low-ILLIQ stocks. Panel B shows that a similar return pattern is also evident for double sorts with respect to $\mathrm{RA_A}$. The return spreads are consistently higher among stocks where limits to arbitrage are most severe. These findings support the theoretical predictions of De Long et al. (1990) and Shleifer and Vishny (1997) for financial anomalies with a behavioral driving force. The overweighting of recent return observations is more likely to induce mispricing if arbitrageurs face higher costs due to illiquidity and volatility.

The empirical results from Table 6 can also be interpreted using the findings of Barber and Odean (2008). They argue that attention-driven noise traders can systematically influence stock market prices. According to Barber and Odean (2008), the noise traders' investment choice set consists of those assets that grab their attention. In a next step, the noise traders choose to buy those stocks from the choice set that look most attractive. As Barber and Odean (2008) show that high absolute returns trigger noise trader attention, stocks with high values of MAX(|ret|) are over-represented in the noise traders' choice sets. Thus, these stocks should be particularly influenced by preferences reflected in $\mathrm{RA_M}$ and $\mathrm{RA_A}$. The double sorts on MAX(|ret|) in Table 6 support this conjecture empirically.

Table 6. Conditional Double Sorts
This table reports monthly value-weighted FFC-adjusted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a quartile portfolio based on ILLIQ, IVOL, or MAX(|ret|). ILLIQ is the Amihud (2002) illiquidity measure based on daily returns of the previous year. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX(|ret|) is the maximum absolute daily return of the previous month. Second, within each quartile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A or based on RA_A in Panel B. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The FFC-adjusted returns are stated in %.

Panel A: Portfolios Sorted by RA_M

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	-0.44	-0.80	-1.16	-2.35	-0.25	-0.60	-0.88	-1.72	-0.23	-0.56	-0.75	-1.55
2	-0.23	-0.20	-0.40	-0.87	-0.02	-0.32	-0.31	-1.27	-0.04	-0.23	-0.52	-1.09
3	-0.00	-0.15	-0.04	-0.34	-0.03	-0.15	-0.12	-0.91	0.07	-0.06	-0.14	-0.96
4	0.05	-0.05	0.11	0.01	0.09	-0.01	-0.05	-0.63	0.21	-0.06	-0.09	-0.34
5	0.04	0.13	0.30	0.18	0.19	0.11	0.05	-0.28	0.23	0.23	-0.11	-0.42
6	0.08	0.15	0.33	0.23	0.07	0.04	0.25	-0.17	0.21	0.11	-0.06	0.05
7	0.08	0.20	0.22	0.35	0.19	0.16	0.09	-0.06	0.08	0.09	0.08	-0.34
8	0.08	0.41	0.55	0.51	0.19	0.20	0.27	0.21	0.25	0.27	0.45	-0.06
9	0.14	0.30	0.38	0.98	0.15	0.10	0.22	0.27	0.26	0.04	0.27	0.22
high	0.23	0.45	0.77	1.01	0.27	0.45	0.75	0.27	0.32	0.53	0.67	0.27
10-1	0.67	1.25	1.93	3.36	0.51	1.05	1.63	1.98	0.54	1.08	1.42	1.82
t(10-1)	(4.25)	(5.45)	(9.03)	(11.45)	(3.86)	(5.18)	(8.50)	(5.97)	(4.20)	(5.87)	(5.50)	(5.87)

Panel B: Portfolios Sorted by RA_A

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	-0.44	-0.52	-0.41	-1.56	-0.38	-0.56	-0.55	-1.36	-0.24	-0.52	-0.48	-1.29
2	-0.27	-0.39	-0.40	-0.61	-0.24	-0.29	-0.19	-0.78	-0.21	-0.30	-0.41	-0.73
3	-0.14	-0.12	-0.05	-0.35	-0.11	-0.14	-0.19	-0.71	0.06	-0.06	-0.30	-0.45
4	-0.20	-0.04	0.00	-0.09	-0.02	-0.08	-0.24	-0.67	-0.08	-0.06	-0.25	-0.64
5	0.10	-0.01	0.24	0.21	0.13	-0.20	0.05	-0.33	0.06	-0.07	-0.04	-0.26
6	0.11	0.20	0.13	0.26	0.26	-0.04	0.08	-0.29	0.20	0.10	-0.12	-0.36
7	0.24	0.28	0.38	0.37	0.15	0.10	0.16	-0.25	0.19	0.11	0.23	-0.27
8	0.21	0.36	0.46	0.51	0.23	0.38	0.34	-0.35	0.44	0.35	0.30	-0.34
9	0.30	0.46	0.58	0.91	0.33	0.39	0.30	0.02	0.42	0.45	0.42	-0.07
high	0.53	0.62	0.51	0.82	0.59	0.62	0.40	0.06	0.68	0.67	0.59	0.02
10-1	0.97	1.15	0.92	2.38	0.97	1.18	0.94	1.42	0.91	1.19	1.07	1.31
t(10-1)	(5.16)	(5.83)	(4.09)	(9.59)	(5.93)	(5.95)	(4.73)	(3.77)	(5.58)	(6.06)	(5.41)	(3.73)

In the Online Appendix, we provide further evidence for a mispricing explanation of our empirical findings. First, we use trading data of NASDAQ stocks to show that the return spreads associated with RA_M and RA_A are larger for stocks with low average trade size. This shows that the return predictability is strongest among the stocks with comparably many small individual investors who are commonly assumed to be most prone to behavioral biases (Han and Kumar, 2013). Second, we apply measures of informed option trading and show that these option measures as proposed by Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing et al. (2010) indeed indicate an overvaluation of stocks with low RA-estimates and an undervaluation if RA-estimates are high based on the demand-based option pricing framework of Garleanu et al. (2009).

Different Specification of RA_M and RA_A. Both Barberis et al. (2016) and Cosemans and Frehen (2017) argue that investors do not judge on historical returns on a stand-alone basis but use reference returns to evaluate a stock's attractiveness. In their empirical base line specification, they therefore consider market excess returns instead of raw returns. The impact of our proposed measure of recency adjustment, however, does not depend on the specific choice of a market-wide reference return. Considering such a reference return r_t^{ref} in Equation (7) would yield

$$RA_{i,t} = Cov_{t,d\in[1,D]}[r_{i,t+1-d} - r_{t+1-d}^{ref}, d] = Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d] - Cov_{t,d\in[1,D]}[r_{t+1-d}^{ref}, d].$$

This shows that the choice of r_t^{ref} influences the magnitude of $RA_{i,t}$ across time, but that the cross-sectional relation is exclusively determined by $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$ such that our cross-sectional analyses yield identical results if investors choose the risk-free rate or the market return as reference point.

Furthermore, the question emerges whether covariance resembles the best statistical concept to reflect our intention of recency adjustment. The covariance term does not only reflect the ordering of returns, but its absolute magnitude also depends on return volatility. We therefore consider correlation coefficients instead of covariances for the calculation of RA_M and RA_A. This implies the advantage that recency adjustment is standardized between -1 and +1 and no longer depends on return volatility. As an additional robustness test, we also apply rank correlation coefficients since they do not carry an implicit linearity assumption as embedded in covariances. Appendix Table 9 shows that both RA_M and RA_A remain significant in Fama-MacBeth-regressions if we use these two alternative specifications.

The Relation Between Recency Adjustment and Reversal. Table 1 shows that RA_A exhibits a strong negative correlation of -46% with REV. Short-term reversal patterns might therefore drive the return predictability of RA_A. The Fama-MacBeth-regressions in Table 5 show that the consideration of REV indeed reduces the RA_A-coefficient, but that RA_A remains significant.[10]

Similar reversal mechanisms might challenge the significance of RA_M. Conrad and Kaul (1989), Lehmann (1990), and Jegadeesh (1990) show that profits of short-term reversal strategies are particularly high for very short formation and holding periods. For example, annualized reversal returns are apparently higher for weekly compared to monthly horizons. Since RA_M reflects the return ordering of the previous month, RA_M and the return of the previous week are by construction negatively correlated. This (untabulated) correlation coefficient is -61% in our sample. Thus, the return predictability associated with RA_M might be due to short-term reversal effects that are not effectively captured by the commonly applied monthly variable REV given that reversal effects are stronger for even shorter formation periods. We therefore also control for the weekly return reversal REV_W in Fama-MacBeth-regressions. Column (4) in Table 7 shows that the consideration of REV_W indeed reduces the magnitude of the RA_M-coefficient (see regression (9) in Table 3 for comparison), but that RA_M retains its significant predictive power for subsequent returns.[11] The consideration of REV_W also alleviates potential concerns that our findings might be driven by short-term trend-chasing behavior: a positive short-term return trend is reflected by high values of REV_W, but not by the ordering of previous returns after controlling for REV_W.

In addition to this empirical verification of robustness, a closer look at Equation (3) theoretically illustrates why previous returns such as reversal or momentum do not capture the recency adjustment effects. According to the first part of Equation (3), previous returns positively influence a stock's perceived attractiveness. This unconditional return effect is complemented by the covariance term reflecting recency effects. Thus, the stand-alone

[10] Untabulated portfolio sorts further support this relationship: If we consider the short-term reversal factor from Kenneth R. French's homepage in addition to the Fama-French-Carhart-factors, the monthly value-weighted decile spread alpha declines from 1.19% to 0.56%, but remains significant (t-statistic of 2.72).

[11] Untabulated analyses reveal that RA_M also remains significant (t-statistic of 9.71) if the return of the last day of month is included as an additional control variable in column (4).

examination of recency adjustment might catch up parts of the previous return impact but it contains additional information as it also takes into account the ordering of returns.

Table 7. Recency Adjustment in Fama-MacBeth-Regressions – Additional Analyses
This table reports Fama-MacBeth-regression estimates based on monthly data from January 1931 to December 2016. The dependent variable is the stock return of the subsequent month. In the first four columns, RA refers to a monthly formation period, while RA refers to an annual formation period in the last four columns. In columns (1) and (5), for each month, small stocks that are below the 20%-size-quantile based on NYSE and AMEX stocks are excluded from the sample. In columns (2) and (6), penny stocks that have a stock price below 5$ are excluded from the sample. In columns (3) and (7), the return of the subsequent month is lagged by one trading day. In columns (4) and (8), the return of the last week (last five trading days) of the formation month is included as additional explanatory variable. The other explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	RA_M				RA_A			
	exclude small caps	exclude penny stocks	skip next day	REV_W as add. control	exclude small caps	exclude penny stocks	skip next day	REV_W as add. control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
intercept	3.3208	3.2233	3.3317	3.1592	3.2157	3.1467	3.2329	2.9823
	(5.89)	(5.78)	(5.40)	(5.05)	(5.70)	(5.77)	(5.34)	(4.87)
RA	0.1443	0.1570	0.1074	0.1247	0.0082	0.0071	0.0099	0.0102
	(15.40)	(17.23)	(15.37)	(13.25)	(2.47)	(2.33)	(3.35)	(3.40)
BETA	0.0906	0.0788	0.0421	0.0336	0.0627	0.0633	0.0309	0.0365
	(0.80)	(0.74)	(0.41)	(0.32)	(0.54)	(0.57)	(0.29)	(0.34)
ln(MV)	-0.1294	-0.1265	-0.1388	-0.1320	-0.1271	-0.1256	-0.1381	-0.1264
	(-4.95)	(-4.87)	(-4.62)	(-4.50)	(-4.80)	(-4.87)	(-4.63)	(-4.37)
BM	0.0547	0.0855	0.0541	0.0752	0.0522	0.0843	0.0547	0.0745
	(1.37)	(2.62)	(2.16)	(2.90)	(1.30)	(2.59)	(2.18)	(2.87)
MOM	0.0080	0.0080	0.0059	0.0065	0.0069	0.0069	0.0049	0.0055
	(4.55)	(5.05)	(2.95)	(3.50)	(3.72)	(4.10)	(2.28)	(2.76)
ltREV	-0.0004	-0.0005	-0.0006	-0.0005	-0.0003	-0.0004	-0.0005	-0.0004
	(-1.46)	(-1.50)	(-1.78)	(-1.46)	(-1.13)	(-1.37)	(-1.51)	(-1.18)
REV	-0.0498	-0.0489	-0.0423	-0.0505	-0.0468	-0.0468	-0.0388	-0.0316
	(-11.25)	(-12.62)	(-11.13)	(-11.81)	(-10.16)	(-11.45)	(-10.02)	(-8.53)
IVOL	-0.4285	-0.5642	0.0807	0.1482	-0.7212	-0.8530	-0.1565	-0.0242
	(-1.16)	(-1.85)	(0.22)	(0.42)	(-1.90)	(-2.71)	(-0.43)	(-0.07)
MAX	0.0048	0.0046	-0.0062	0.0084	0.0064	0.0055	-0.0045	0.0128
	(0.41)	(0.41)	(-0.50)	(0.68)	(0.54)	(0.49)	(-0.36)	(1.04)
MIN	0.0799	0.0786	0.0782	0.0938	0.0652	0.0624	0.0634	0.0853
	(6.09)	(6.35)	(6.20)	(7.46)	(4.85)	(4.94)	(4.98)	(6.72)
ILLIQ	0.0608	0.0198	0.0235	0.0210	0.0653	0.0185	0.0231	0.0211
	(1.07)	(2.09)	(3.45)	(3.18)	(1.11)	(1.93)	(3.42)	(3.23)
RR	0.4144	0.4815	0.5601	0.6099	0.4871	0.5309	0.6684	0.6790
	(4.37)	(5.73)	(6.32)	(6.74)	(5.63)	(7.40)	(7.28)	(7.43)
TK	-2.7418	-2.5557	-3.2629	-3.3643	-2.9823	-2.6290	-3.3526	-3.3645
	(-1.75)	(-1.78)	(-2.14)	(-2.17)	(-1.90)	(-1.83)	(-2.19)	(-2.16)
ST	-0.0347	-0.0493	-0.0631	-0.0721	-0.0280	-0.0370	-0.0570	-0.0688
	(-2.27)	(-3.90)	(-4.09)	(-4.91)	(-1.83)	(-2.86)	(-3.61)	(-4.66)
REV_W				-0.0698				-0.1300
				(-8.70)				(-19.71)

The discussed reversal patterns are also frequently explained by bid-ask-bounce or stock illiquidity (Conrad et al., 1997; Avramov et al., 2006).[12] However, columns (1), (2), (5), and (6) of Table 7 show that the influence of RA_M and RA_A remains significant after eliminating small and penny stocks from our sample that are presumably most affected by potential micro-structure concerns.[13] In addition, we address these concerns by skipping one day after the formation period before measuring the subsequent returns. Columns (3) and (7) show that both RA_M and RA_A remain significant.

Examination of Subperiods. Finally, we also examine whether the empirical findings are representative for two subperiods of our sample. We find that the return patterns associated with RA_M and RA_A are highly significant both in the first half our sample from 1931 to 1973 and in the second half from 1974 to 2016. The analyses provided in the Online Appendix show that the monthly decile return spreads exceed 1% in both subperiods for value-weighted, equally-weighted, raw, and FFC-adjusted returns. For RA_M, the return spreads are slightly higher in the second half of the sample, while RA_A shows slightly stronger predictability for the first half of the sample. These significant relationships can also be supported for both subperiods using Fama-MacBeth-regressions.

Alternative Behavioral Mechanism. The previous paragraphs emphasize the relevance of RA_M and RA_A from an empirical perspective. The results are valid beyond micro-structure effects and challenge the weak form of the efficient market hypothesis since the ordering of returns can hardly be interpreted as a proxy for risk. While the analyses thus directly point at a behavioral explanation for the apparent return predictability, the exact behavioral driving force warrants further discussion. We conjecture that systematic patterns of mispricing emerge, since investors use past returns as a representation for future returns. This is in line with recent literature arguing that investors have preferences for stocks with high past MAX values (Bali et al., 2011), high salient past returns (Cosemans and Frehen, 2017) or high realized CPT-values (Barberis et al., 2016). In addition to these time-independent effects, we argue that recent returns receive higher weight leading to the return predictability

[12]Also see more recent analyses by de Groot et al. (2012) and Blitz et al. (2013) who argue that trading strategies based on short-term reversal can remain profitable after taking these micro-structure effects and trading costs into account.

[13]We consider stocks as small caps if they fall below the 20%-size-quantile of NYSE and AMEX stocks (Nagel, 2005). Stocks are classified as penny stocks if their share price is below 5$.

of recency adjustment after controlling for the various time-independent previous return measures.

One challenge for this entire strand of literature is that the apparent mispricing is not necessarily attributable to investors looking at historical returns; it might also emerge as the historical returns themselves could be affected by systematic overreaction. For example, the overvaluation associated with MAX could either be due to investors who buy high-MAX stocks because of the attractive lottery-like payoff or due to investor overreaction that is strongest for the most positive news that lead to the highest MAX return. Similarly, investors might also overreact towards the most salient news that lead to the most salient returns. This could explain why salient returns tend to reverse, that is, why high ST-values trigger low subsequent returns.[14]

In our opinion, recency adjustment should be less influenced by these potential overreaction mechanisms since investors presumably do not systematically underreact towards information at the beginning of a month and overreact at the end of a month. However, our findings on $\mathrm{RA_M}$ might still be affected if there is a general overreaction towards news which is corrected within the subsequent days. In this case, the subsequent price correction would be particularly influenced by the most recent returns. However, $\mathrm{RA_M}$ does not only reflect these recent returns but the return ordering of the previous month. As it remains significant after controlling for the most recent return $\mathrm{REV_W}$ in Table 7, $\mathrm{RA_M}$ seems to reflect more than a potential overvaluation due to short-term overreaction. Similarly, the analyses show that $\mathrm{RA_A}$ contains information beyond the potential overvaluation associated with REV. In conclusion, we therefore consider it as most likely that the reported return predictability is indeed driven by investors who use previous returns as a representation for future returns.

[14]Empirically, these two potential mechanisms are hard to distinguish. Although beyond the scope of the empirical literature strand applying this representation hypothesis, its further investigation thus appears to be a promising area for future research. For example, field studies or experiments might help to unambiguously identify those return characteristic measures that are most strongly linked to investors' perception of stock attractiveness. Corresponding research could help to more clearly link the empirical findings to either a biased reaction towards news or the representation hypothesis.

5. Conclusion

Barberis et al. (2016) argue that financial decision makers use past returns as representation for a stock's future returns. They put forward that further research should examine how this representation is used by investors beyond their examination of CPT implications. We take a first step in this direction. We conjecture that investors put stronger emphasize on recent returns compared to more distant returns in their formation of beliefs. Investors should thus prefer stocks with high recent and low distant returns over stocks with low recent and high distant returns. In order to capture these ordering effects in past returns, we introduce a measure of recency adjustment RA. RA takes on low values if recent returns are high in comparison to more distant returns. Hence, low-RA stocks should be perceived as more attractive, should be more prone to overvaluation, and should yield lower subsequent returns.

We empirically support the hypothesis that RA and subsequent returns are positively related. Estimating RA based on the ordering of daily returns of the previous month, high-RA stocks outperform low-RA stocks by 1.20% on a monthly Fama-French-Carhart-adjusted basis using value-weighted decile portfolios. This return premium has a similar magnitude if RA is calculated using monthly returns of the previous year. Conditional double sorts and Fama-MacBeth-regressions show that the return premiums are not captured by other known return predictors. These findings are valid beyond small and penny stocks and cannot be explained by micro-structure effects. Further analyses support the conjectured behavioral driving force since the return spreads increase if limits to arbitrage are stonger.

Our research thus supports the hypothesis that investors' financial decision making relies too much on historical return patterns. In this context, Barberis et al. (2016) show the relevance of evaluation biases as CPT-values can be used to identify mispriced stocks. We show that the processing of previous return information is also affected by judgment biases. Investors overestimate the representativeness of recent observations and thereby underweight distant observations in their belief formation process. Hence, the recency biases detected in laboratory experiments have implications beyond their impact on individual decision making. These specific judgment biases also seem to influence real market prices and can therefore cause cross-sectional return predictability.

6. Appendix

Table 8 shows that the return spreads associated with RA_M and RA_A are significant after accounting for the control variables introduced in Table 1 in conditional double portfolio sorts.

Table 8. Double Sorts based on Recency Adjustment
This table reports monthly FFC-adjusted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a decile portfolio based on one of the control variables BETA, ln(MV), BM, MOM, ltREV, REV, IVOL, MAX, MIN, ILLIQ, RR, TK, or ST as introduced in Table 1. Second, within each decile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A and RA_A in Panel B. RA_M is the recency adjustment for the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. For each of the resulting 100 portfolios, the value-weighted return is calculated. These 100 portfolio returns are then aggregated across the first sorting criterion, that is, the reported RA-decile returns are computed as the average return among the ten corresponding portfolios sorted by one of the control variables. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

Panel A: Monthly Recency Adjustment RA_M

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	-0.81	-1.17	-0.88	-1.02	-0.87	-0.72	-0.86	-0.78	-0.89	-1.17	-0.83	-0.91	-0.73
2	-0.25	-0.35	-0.34	-0.36	-0.30	-0.36	-0.52	-0.44	-0.40	-0.42	-0.40	-0.38	-0.46
3	-0.10	-0.09	-0.09	-0.19	-0.18	-0.14	-0.35	-0.35	-0.24	-0.15	-0.14	-0.07	-0.15
4	-0.09	0.08	0.04	-0.05	-0.01	-0.05	-0.17	-0.08	-0.00	0.05	-0.03	0.08	-0.03
5	0.05	0.19	0.14	0.18	0.09	0.09	-0.01	-0.06	0.04	0.14	0.04	0.22	-0.04
6	0.08	0.32	0.12	0.09	0.11	0.13	0.01	-0.03	0.07	0.21	0.10	0.18	0.13
7	0.07	0.30	0.26	0.18	0.12	0.11	0.15	0.03	0.13	0.31	0.09	0.23	0.10
8	0.09	0.46	0.28	0.20	0.20	0.31	0.24	0.17	0.15	0.38	0.22	0.28	0.13
9	0.27	0.56	0.44	0.28	0.26	0.34	0.23	0.20	0.27	0.50	0.20	0.31	0.33
high	0.46	0.61	0.60	0.40	0.54	0.46	0.49	0.56	0.39	0.62	0.36	0.54	0.45
10-1	1.26	1.78	1.48	1.42	1.41	1.18	1.35	1.34	1.28	1.79	1.20	1.45	1.18
t(10-1)	(10.79)	(10.77)	(9.03)	(9.35)	(9.45)	(7.49)	(8.29)	(8.84)	(9.23)	(10.97)	(9.21)	(8.35)	(8.29)

Panel B: Annual Recency Adjustment RA_A

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	-0.61	-0.75	-0.60	-0.65	-0.72	-0.41	-0.65	-0.66	-0.74	-0.75	-0.60	-0.65	-0.57
2	-0.47	-0.35	-0.30	-0.46	-0.33	-0.18	-0.35	-0.36	-0.43	-0.34	-0.42	-0.33	-0.32
3	-0.24	-0.16	-0.19	-0.31	-0.21	-0.20	-0.28	-0.29	-0.26	-0.16	-0.24	-0.12	-0.28
4	-0.17	-0.01	-0.08	-0.09	-0.09	-0.03	-0.27	-0.18	-0.16	-0.08	-0.10	-0.09	-0.14
5	-0.00	0.17	0.08	0.04	-0.08	0.02	-0.08	-0.06	-0.10	0.11	-0.07	0.07	-0.06
6	0.14	0.20	0.18	0.15	0.08	0.05	-0.02	-0.03	0.04	0.18	0.14	0.20	0.07
7	0.18	0.33	0.24	0.22	0.18	0.17	0.07	0.12	0.16	0.30	0.26	0.27	0.29
8	0.35	0.41	0.39	0.31	0.27	0.20	0.19	0.14	0.24	0.43	0.27	0.37	0.23
9	0.43	0.51	0.58	0.53	0.45	0.28	0.33	0.26	0.34	0.57	0.43	0.40	0.35
high	0.73	0.62	0.77	0.59	0.64	0.47	0.48	0.51	0.55	0.64	0.62	0.61	0.47
10-1	1.34	1.38	1.37	1.24	1.36	0.88	1.12	1.17	1.29	1.39	1.21	1.26	1.04
t(10-1)	(8.52)	(8.14)	(7.50)	(6.07)	(7.22)	(4.95)	(6.91)	(7.38)	(8.32)	(8.24)	(7.07)	(7.01)	(6.25)

Table 9 shows that Fama-MacBeth-regression coefficients for RA_M and RA_A remain significant if they are calculated based on (rank) correlation coefficients instead of covariance. Further, the Online Appendix shows that the (rank) correlation-based versions of RA_M and RA_A yield monthly decile return spreads of at least 0.74% across various portfolio return measurement specifications.

Table 9. Correlation-Based Recency Adjustment in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. In the first two columns, RA refers to a monthly formation period, while RA refers to an annual formation period in the last two columns. In the first and the third column, RA is based on the correlation of past returns with the remaining time until portfolio formation. In the second and the fourth column, RA is based on the rank correlation of past returns with the remaining time until portfolio formation. The other explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	RA_M based on		RA_A based on	
	correlation	rank correlation	correlation	rank correlation
intercept	3.1828	3.1342	3.0427	3.0585
	(5.14)	(5.03)	(4.91)	(4.96)
RA	2.7945	2.5363	0.4990	0.2912
	(12.97)	(14.30)	(4.12)	(2.68)
BETA	0.0352	0.0382	0.0330	0.0272
	(0.33)	(0.36)	(0.31)	(0.26)
ln(MV)	-0.1372	-0.1358	-0.1357	-0.1349
	(-4.66)	(-4.59)	(-4.60)	(-4.62)
BM	0.0816	0.0815	0.0804	0.0809
	(3.07)	(3.06)	(3.05)	(3.06)
MOM	0.0061	0.0060	0.0050	0.0051
	(3.18)	(3.14)	(2.48)	(2.54)
ltREV	-0.0005	-0.0004	-0.0004	-0.0004
	(-1.25)	(-1.20)	(-1.02)	(-1.00)
REV	-0.0663	-0.0658	-0.0632	-0.0640
	(-15.59)	(-15.51)	(-14.64)	(-15.02)
IVOL	0.1132	0.0950	-0.0891	-0.0785
	(0.32)	(0.27)	(-0.25)	(-0.22)
MAX	0.0069	0.0060	0.0080	0.0073
	(0.55)	(0.49)	(0.65)	(0.59)
MIN	0.0864	0.0825	0.0746	0.0756
	(6.64)	(6.20)	(5.72)	(5.83)
ILLIQ	0.0195	0.0194	0.0200	0.0201
	(3.06)	(3.06)	(3.10)	(3.10)
RR	0.6647	0.6671	0.7656	0.7427
	(7.01)	(7.10)	(8.68)	(8.17)
TK	-3.5920	-3.5561	-3.7927	-3.8967
	(-2.27)	(-2.24)	(-2.37)	(-2.42)
ST	-0.0713	-0.0705	-0.0647	-0.0642
	(-4.71)	(-4.62)	(-4.19)	(-4.18)

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Online Appendix for

"The Impact of Recency Effects on Stock Market Prices"

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1. Additional Summary Statistics

Table 1 provides summary statistics and correlation coefficients for all relevant variables similar to Table 1 of the main paper. However, while we present pooled summary statistics in the main paper, this Online Appendix table shows time-series averages of monthly cross-sectional summary statistics. In addition, applying decile portfolio sorts based on RA_M and RA_A, Table 2 presents average portfolio values for all variables introduced in Table 1 of the main paper.

Table 1. Summary Statistics
This table reports time-series averages of monthly cross-sectional sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients for the main variables of the analyses. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. MV is the market value of equity. BM denotes the book-to-market ratio. MOM, ltREV, and REV are the returns of months $t-12$ to $t-2$, $t-60$ to $t-13$, and $t-1$, respectively. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX and MIN denote the maximum and minimum daily return of the previous month, respectively. Amihud (2002) illiquidity measure, ILLIQ, and market beta, BETA, are estimated over the previous year. RR is the recency ratio as introduced by Bhootra and Hur (2013). TK denotes the TK-value as proposed by Barberis et al. (2016). ST reflects the salience theory value of Cosemans and Frehen (2017). ILLIQ is stated in million; RA_M, RA_A, ltREV, REV, MAX, MIN, and ST are stated in %. The sample period is from January 1931 to December 2016.

	RA_M	RA_A	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
mean	0.17	0.00	0.97	18.32	1.43	15.09	81.25	1.33	0.34	6.09	-4.98	7.42	0.55	-0.05	0.54
SD	3.63	11.64	0.56	1.80	2.75	43.57	157.73	11.17	0.26	5.58	3.50	36.78	0.30	0.03	2.48
$q_{0.1}$	-3.53	-12.47	0.30	16.02	0.31	-25.64	-35.21	-9.92	0.14	2.17	-8.80	0.07	0.14	-0.09	-1.80
$q_{0.5}$	0.15	-0.02	0.92	18.25	0.88	8.98	47.06	0.53	0.27	4.69	-4.12	0.70	0.57	-0.05	0.28
$q_{0.9}$	3.86	12.56	1.72	20.70	2.54	58.57	217.44	12.92	0.61	11.16	-2.00	11.97	0.92	-0.02	3.08

Correlation coefficients															
RA_M	1.00														
RA_A	0.01	1.00													
BETA	0.01	0.05	1.00												
ln(MV)	-0.01	-0.01	0.12	1.00											
BM	0.02	0.01	-0.01	-0.28	1.00										
MOM	-0.03	0.14	0.06	0.11	-0.19	1.00									
ltREV	-0.01	0.01	0.11	0.18	-0.18	-0.01	1.00								
REV	0.04	-0.45	-0.01	0.04	-0.08	0.01	-0.01	1.00							
IVOL	0.01	-0.07	0.13	-0.51	0.23	-0.10	-0.12	0.13	1.00						
MAX	0.02	-0.15	0.17	-0.39	0.18	-0.07	-0.09	0.31	0.87	1.00					
MIN	-0.01	-0.07	-0.20	0.43	-0.23	0.06	0.09	0.19	-0.78	-0.57	1.00				
ILLIQ	0.00	-0.05	-0.11	-0.37	0.22	-0.05	-0.12	0.01	0.42	0.32	-0.33	1.00			
RR	0.02	-0.09	-0.04	0.20	-0.16	0.52	0.00	0.14	-0.14	-0.08	0.14	-0.08	1.00		
TK	-0.01	-0.01	0.00	0.36	-0.30	0.32	0.56	0.11	-0.31	-0.22	0.29	-0.19	0.27	1.00	
ST	0.02	-0.29	0.07	-0.12	0.03	-0.02	-0.04	0.63	0.43	0.66	0.03	0.14	0.04	-0.03	1.00

Table 2. Characteristics of Decile Portfolios

This table reports monthly decile portfolio sorts based on monthly recency adjustment, RA_M, in Panel A and annual recency adjustment, RA_A, in Panel B for the sample period from January 1931 to December 2016. The table presents portfolio averages for all the variables introduced in Table 1 of the main paper. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: Decile Portfolio Sorts based on RA_M

	RA_M	RA_A	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	-6.09	-1.29	1.06	17.55	2.02	17.08	77.50	2.88	0.54	9.92	-7.32	18.03	0.51	-0.06	1.42
2	-2.69	0.21	0.99	18.24	1.34	16.58	84.57	0.57	0.34	6.02	-5.11	6.18	0.54	-0.05	0.43
3	-1.57	0.38	0.95	18.49	1.24	15.84	84.11	0.36	0.29	5.15	-4.50	5.11	0.55	-0.05	0.26
4	-0.80	0.40	0.92	18.62	1.20	15.07	82.44	0.31	0.27	4.71	-4.16	3.74	0.56	-0.05	0.19
5	-0.16	0.33	0.91	18.68	1.19	14.72	81.47	0.42	0.26	4.53	-4.01	3.78	0.56	-0.05	0.18
6	0.45	0.38	0.91	18.68	1.20	14.71	81.15	0.52	0.26	4.55	-4.01	3.86	0.57	-0.05	0.20
7	1.10	0.26	0.93	18.64	1.22	14.36	81.79	0.85	0.27	4.76	-4.12	4.08	0.56	-0.05	0.25
8	1.88	0.21	0.97	18.53	1.28	14.35	83.62	1.17	0.29	5.18	-4.40	4.29	0.56	-0.05	0.35
9	3.02	0.14	1.01	18.26	1.42	14.43	82.66	1.71	0.34	6.04	-4.99	6.09	0.55	-0.05	0.54
high	6.53	-0.99	1.07	17.52	2.19	13.78	73.16	4.53	0.54	10.01	-7.22	19.01	0.53	-0.06	1.57
10-1	12.61	0.30	0.02	-0.03	0.18	-3.31	-4.34	1.64	-0.00	0.08	0.10	0.98	0.02	-0.00	0.15
t(10-1)	(27.51)	(1.99)	(1.24)	(-1.26)	(2.36)	(-6.19)	(-2.39)	(8.10)	(-0.84)	(0.65)	(1.55)	(0.93)	(5.74)	(-3.96)	(3.54)

Panel B: Decile Portfolio Sorts based on RA_A

	RA_M	RA_A	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	0.19	-20.36	1.05	17.69	1.73	13.05	77.34	12.10	0.50	10.00	-5.98	19.23	0.58	-0.06	2.37
2	0.16	-9.77	0.97	18.26	1.41	9.37	81.98	5.30	0.35	6.61	-4.76	8.21	0.57	-0.05	1.08
3	0.17	-6.00	0.93	18.48	1.28	10.02	81.65	3.39	0.31	5.71	-4.38	5.58	0.57	-0.05	0.71
4	0.16	-3.33	0.91	18.59	1.25	10.60	80.52	2.17	0.29	5.30	-4.24	4.94	0.57	-0.05	0.51
5	0.17	-1.09	0.90	18.63	1.25	11.48	80.09	1.18	0.28	5.05	-4.23	4.54	0.56	-0.05	0.37
6	0.16	1.05	0.91	18.64	1.26	12.83	80.52	0.33	0.28	4.95	-4.29	4.54	0.56	-0.05	0.26
7	0.14	3.31	0.92	18.59	1.30	14.27	80.15	-0.62	0.29	4.99	-4.47	4.14	0.55	-0.05	0.16
8	0.16	5.99	0.96	18.48	1.32	16.01	82.88	-1.61	0.30	5.17	-4.78	4.78	0.53	-0.05	0.07
9	0.17	9.79	1.02	18.25	1.43	19.32	84.69	-2.98	0.34	5.70	-5.41	5.90	0.52	-0.05	-0.02
high	0.18	20.45	1.16	17.60	2.06	33.98	82.62	-5.95	0.46	7.39	-7.30	12.29	0.48	-0.06	-0.12
10-1	-0.01	40.81	0.11	-0.09	0.33	20.92	5.28	-18.05	-0.04	-2.61	-1.32	-6.95	-0.09	-0.00	-2.49
t(10-1)	(-0.18)	(26.95)	(4.43)	(-2.25)	(3.12)	(9.66)	(1.47)	(-24.37)	(-5.56)	(-13.40)	(-9.20)	(-3.90)	(-9.91)	(-2.50)	(-24.37)

2. Recency Adjustment Based on Specific Value and Weighting Functions

In Chapter 3 of the main paper, we define recency adjustment as the covariance between returns and past time (see Equation (7) in the main paper). This approach reflects the positive slope of the value function $v(r)$ and the negative slope of the weighting function $w(d)$. However, it ignores potential higher order impacts in order to avoid doubtful assumptions on the specific functional forms of $v(r)$ and $w(d)$. In this chapter, we examine the special case of a prospect theory value function and an exponential weighting function, that is, we use $Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)]$ instead of $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$ as a measure of recency adjustment. Following Barberis et al. (2016), we use

$$v(r) = \begin{cases} r^{\alpha} & \text{for } r \geq 0 \\ -\lambda(-r)^{\alpha} & \text{for } r < 0 \end{cases} \qquad \text{and} \qquad w(d) = \delta^{d}.$$

In line with experimental evidence from Tversky and Kahneman (1992), we set $\alpha = 0.88$ and $\lambda = 2.25$. Since Barberis et al. (2016) consider a δ-range from 0.8 to 0.95 on a monthly basis, we equivalently examine the cases $\delta = 0.8$, $\delta = 0.85$, $\delta = 0.9$, and $\delta = 0.95$. The corresponding estimates for monthly recency adjustment based on daily data are denoted as $\mathrm{RA}_{\mathrm{M}}^{0.8}$, $\mathrm{RA}_{\mathrm{M}}^{0.85}$, $\mathrm{RA}_{\mathrm{M}}^{0.9}$, and $\mathrm{RA}_{\mathrm{M}}^{0.95}$, respectively. The annual recency adjustment estimates based on monthly data are $\mathrm{RA}_{\mathrm{A}}^{0.8}$, $\mathrm{RA}_{\mathrm{A}}^{0.85}$, $\mathrm{RA}_{\mathrm{A}}^{0.9}$, and $\mathrm{RA}_{\mathrm{A}}^{0.95}$, respectively.

Summary statistics and correlation coefficients are provided in Table 3. The four different δ-settings seem to play a very minor role since the corresponding $\mathrm{RA}_{\mathrm{M}}^{\delta}$- and $\mathrm{RA}_{\mathrm{A}}^{\delta}$-estimates are nearly perfectly correlated. Moreover, the respective correlation with the baseline specifications RA_{M} and RA_{A} is a least 0.9 in absolute terms.[1] This shows that large parts of $Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)]$ are well reflected by $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$. In the specifications of Barberis et al. (2016), higher order moments of $v(r)$ and $w(d)$ thus seem to play a minor role with respect to recency adjustment such that RA_{M} and RA_{A} are adequate proxies for recency effects.

[1]The negative correlation is due to the negative slope of the weighting function which implies that $Cov_{t,d\in[1,D]}[r_{i,t+1-d}, d]$ negatively influences $Cov_{t,d\in[1,D]}[v(r_{i,t+1-d}), w(d)]$ according to Equation (6) in the main paper.

Table 3. Summary Statistics for Different Specifications of Recency Adjustment
This table reports pooled sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients for different specifications of recency adjustment. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The other versions of RA refer to the covariance between return values and corresponding observation weight. The value function is based on prospect theory preferences. The weighting function is exponential such that more distant observations are down-weighted by the factor 0.8, 0.85, 0.9, or 0.95 per month, respectively. The sample period is from January 1931 to December 2016.

	RA_M	$RA_M^{0.8}$	$RA_M^{0.85}$	$RA_M^{0.9}$	$RA_M^{0.95}$	RA_A	$RA_A^{0.8}$	$RA_A^{0.85}$	$RA_A^{0.9}$	$RA_A^{0.95}$
mean	-0.00	0.00	0.00	0.00	0.00	0.07	-0.01	-0.01	-0.01	-0.01
SD	4.68	0.09	0.07	0.05	0.02	15.83	1.78	1.74	1.52	1.01
$q_{0.1}$	-4.44	-0.10	-0.07	-0.05	-0.02	-15.76	-2.03	-1.97	-1.72	-1.14
$q_{0.5}$	0.03	-0.00	-0.00	-0.00	-0.00	0.10	0.03	0.02	0.01	0.00
$q_{0.9}$	4.36	0.10	0.07	0.05	0.02	16.02	1.93	1.89	1.67	1.12
Correlation coefficients										
RA_M	1.00									
$RA_M^{0.8}$	-0.90	1.00								
$RA_M^{0.85}$	-0.90	1.00	1.00							
$RA_M^{0.9}$	-0.90	1.00	1.00	1.00						
$RA_M^{0.95}$	-0.90	1.00	1.00	1.00	1.00					
RA_A	-0.03	0.01	0.01	0.01	0.01	1.00				
$RA_A^{0.8}$	0.04	-0.01	-0.01	-0.01	-0.01	-0.90	1.00			
$RA_A^{0.85}$	0.03	-0.01	-0.01	-0.01	-0.01	-0.92	1.00	1.00		
$RA_A^{0.9}$	0.03	-0.01	-0.01	-0.01	-0.01	-0.93	0.99	1.00	1.00	
$RA_A^{0.95}$	0.03	-0.01	-0.01	-0.01	-0.01	-0.94	0.97	0.99	1.00	1.00

Further supporting this argument, Tables 4 and 5 show that RA_M^{δ} and RA_A^{δ} have similar predictive power for subsequent returns as RA_M and RA_A.[2]

[2]Note that – in contrast to RA_M and RA_A – RA_M^{δ} and RA_A^{δ} should negatively predict subsequent returns since they positively influence the stock's perceived attractiveness (see Equation (3) in the main paper).

Table 4. Portfolio Sorts Based on Different Specifications of Recency Adjustment
This table reports monthly decile portfolio sorts based on different specifications of recency adjustment RA. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The other versions of RA refer to the covariance between return values and corresponding observation weight. The value function is based on prospect theory preferences. The weighting function is exponential such that more distant observations are down-weighted by the factor 0.8, 0.85, 0.9, or 0.95 per month, respectively. Subsequent Fama-French-Carhart-adjusted returns are provided for equally- and value-weighted portfolios in Panels A and B, respectively. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Fama-French-Carhart-adjusted returns are stated in %.

Panel A: Equally-Weighted Returns

	Monthly Recency Adjustment					Annual Recency Adjustment				
	RA_M	$RA_M^{0.8}$	$RA_M^{0.85}$	$RA_M^{0.9}$	$RA_M^{0.95}$	RA_A	$RA_A^{0.8}$	$RA_A^{0.85}$	$RA_A^{0.9}$	$RA_A^{0.95}$
low	-1.16	1.15	1.15	1.14	1.13	-0.87	1.28	1.26	1.22	1.20
2	-0.24	0.52	0.50	0.50	0.50	-0.37	0.59	0.57	0.55	0.54
3	0.01	0.40	0.40	0.39	0.40	-0.18	0.41	0.42	0.44	0.42
4	0.12	0.25	0.25	0.26	0.25	0.04	0.21	0.23	0.26	0.30
5	0.26	0.14	0.15	0.14	0.14	0.09	0.16	0.17	0.14	0.14
6	0.17	0.14	0.14	0.16	0.16	0.19	0.03	0.03	0.07	0.05
7	0.29	0.02	0.00	0.01	0.00	0.31	-0.08	-0.10	-0.14	-0.13
8	0.35	-0.07	-0.06	-0.06	-0.06	0.45	-0.18	-0.16	-0.13	-0.13
9	0.50	-0.30	-0.30	-0.31	-0.30	0.59	-0.31	-0.31	-0.33	-0.32
high	0.95	-0.99	-0.98	-0.97	-0.97	1.01	-0.86	-0.84	-0.83	-0.82
10-1	2.12	-2.14	-2.13	-2.12	-2.10	1.88	-2.15	-2.11	-2.04	-2.01
t(10-1)	(11.81)	(-11.77)	(-11.73)	(-11.60)	(-11.61)	(8.84)	(-9.42)	(-9.13)	(-9.02)	(-8.87)

Panel B: Value-Weighted Returns

	Monthly Recency Adjustment					Annual Recency Adjustment				
	RA_M	$RA_M^{0.8}$	$RA_M^{0.85}$	$RA_M^{0.9}$	$RA_M^{0.95}$	RA_A	$RA_A^{0.8}$	$RA_A^{0.85}$	$RA_A^{0.9}$	$RA_A^{0.95}$
low	-0.86	0.42	0.42	0.43	0.43	-0.63	0.63	0.61	0.59	0.64
2	-0.26	0.14	0.13	0.14	0.14	-0.34	0.45	0.49	0.48	0.44
3	-0.16	0.21	0.22	0.21	0.19	-0.27	0.27	0.25	0.28	0.32
4	-0.01	-0.01	-0.01	0.00	0.02	-0.07	0.20	0.21	0.22	0.24
5	0.14	0.10	0.09	0.09	0.10	-0.07	0.08	0.06	0.02	0.03
6	0.04	0.13	0.12	0.13	0.14	0.15	-0.06	-0.07	-0.13	-0.12
7	0.07	-0.09	-0.07	-0.06	-0.06	0.23	-0.08	-0.10	-0.03	-0.05
8	0.18	-0.01	-0.01	-0.01	-0.00	0.32	-0.15	-0.19	-0.25	-0.24
9	0.16	-0.39	-0.41	-0.40	-0.39	0.42	-0.36	-0.36	-0.36	-0.40
high	0.33	-0.63	-0.64	-0.63	-0.63	0.56	-0.70	-0.69	-0.69	-0.67
10-1	1.20	-1.05	-1.06	-1.06	-1.06	1.19	-1.33	-1.30	-1.28	-1.31
t(10-1)	(6.29)	(-5.88)	(-5.85)	(-5.79)	(-5.75)	(6.00)	(-6.43)	(-6.25)	(-6.01)	(-5.90)

Table 5. Different Specifications of Recency Adjustment in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates based on monthly data. The dependent variable is the stock return of the subsequent month. RA refers to recency adjustment while the exact specification differs between columns. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The other versions of RA refer to the covariance between return values and corresponding observation weight. The value function is based on prospect theory preferences. The weighting function is exponential such that more distant observations are down-weighted by the factor 0.8, 0.85, 0.9, or 0.95 per month, respectively. All RA_M^{δ}-estimates (RA_A^{δ}-estimates) are standardized to have the same standard deviation as RA_M (RA_A). The other explanatory variables are described in Table 1. The sample period is January 1931 to December 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	RA_M	$RA_M^{0.8}$	$RA_M^{0.85}$	$RA_M^{0.9}$	$RA_M^{0.95}$	RA_A	$RA_A^{0.8}$	$RA_A^{0.85}$	$RA_A^{0.9}$	$RA_A^{0.95}$
intercept	3.1194	3.1482	3.1486	3.1490	3.1494	3.0098	3.0402	3.0378	3.0359	3.0346
	(5.00)	(5.05)	(5.05)	(5.05)	(5.05)	(4.90)	(5.02)	(5.00)	(4.98)	(4.96)
RA	0.1930	-0.1810	-0.1800	-0.1791	-0.1782	0.0120	-0.0132	-0.0126	-0.0121	-0.0117
	(23.58)	(-21.75)	(-21.79)	(-21.84)	(-21.88)	(3.96)	(-3.95)	(-3.92)	(-3.91)	(-3.91)
BETA	0.0280	0.0363	0.0359	0.0355	0.0351	0.0235	0.0225	0.0218	0.0211	0.0206
	(0.27)	(0.35)	(0.34)	(0.34)	(0.33)	(0.21)	(0.21)	(0.20)	(0.19)	(0.19)
ln(MV)	-0.1314	-0.1327	-0.1327	-0.1328	-0.1329	-0.1315	-0.1326	-0.1325	-0.1324	-0.1322
	(-4.46)	(-4.51)	(-4.52)	(-4.52)	(-4.52)	(-4.49)	(-4.57)	(-4.56)	(-4.54)	(-4.53)
BM	0.0760	0.0742	0.0742	0.0743	0.0743	0.0798	0.0806	0.0804	0.0802	0.0799
	(2.91)	(2.84)	(2.84)	(2.85)	(2.85)	(3.04)	(3.06)	(3.06)	(3.05)	(3.04)
MOM	0.0063	0.0064	0.0064	0.0064	0.0064	0.0048	0.0050	0.0050	0.0050	0.0050
	(3.32)	(3.30)	(3.29)	(3.29)	(3.29)	(2.34)	(2.45)	(2.45)	(2.45)	(2.45)
ltREV	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(-1.37)	(-1.27)	(-1.27)	(-1.27)	(-1.26)	(-1.04)	(-1.12)	(-1.11)	(-1.09)	(-1.08)
REV	-0.0670	-0.0665	-0.0665	-0.0666	-0.0666	-0.0621	-0.0581	-0.0592	-0.0601	-0.0609
	(-15.75)	(-15.70)	(-15.70)	(-15.70)	(-15.69)	(-14.68)	(-12.97)	(-13.40)	(-13.78)	(-14.10)
IVOL	0.1701	0.2164	0.2166	0.2168	0.2169	-0.1471	-0.1490	-0.1523	-0.1554	-0.1580
	(0.48)	(0.61)	(0.61)	(0.61)	(0.61)	(-0.41)	(-0.42)	(-0.43)	(-0.44)	(-0.44)
MAX	0.0071	0.0046	0.0045	0.0045	0.0044	0.0090	0.0087	0.0088	0.0089	0.0089
	(0.56)	(0.37)	(0.36)	(0.36)	(0.36)	(0.72)	(0.70)	(0.71)	(0.71)	(0.72)
MIN	0.0919	0.0956	0.0956	0.0956	0.0956	0.0737	0.0753	0.0754	0.0755	0.0756
	(7.14)	(7.36)	(7.37)	(7.37)	(7.36)	(5.60)	(5.75)	(5.76)	(5.77)	(5.78)
ILLIQ	0.0204	0.0204	0.0204	0.0204	0.0204	0.0200	0.0202	0.0202	0.0201	0.0201
	(3.15)	(3.18)	(3.18)	(3.18)	(3.17)	(3.10)	(3.14)	(3.13)	(3.13)	(3.12)
RR	0.6323	0.6221	0.6229	0.6238	0.6246	0.7831	0.7229	0.7290	0.7353	0.7415
	(6.71)	(6.56)	(6.57)	(6.58)	(6.59)	(8.53)	(7.87)	(7.93)	(8.00)	(8.06)
TK	-3.4459	-3.5415	-3.5423	-3.5431	-3.5438	-3.6089	-3.7828	-3.7565	-3.7315	-3.7094
	(-2.20)	(-2.26)	(-2.26)	(-2.26)	(-2.26)	(-2.29)	(-2.37)	(-2.36)	(-2.35)	(-2.34)
ST	-0.0732	-0.0743	-0.0743	-0.0743	-0.0743	-0.0646	-0.0626	-0.0630	-0.0634	-0.0636
	(-4.92)	(-5.02)	(-5.01)	(-5.01)	(-5.01)	(-4.17)	(-4.09)	(-4.11)	(-4.12)	(-4.13)

3. Different Specifications of Fama-MacBeth-regressions

This chapter presents different specifications for the Fama-MacBeth-regressions presented in Tables 3 and 5 of the main paper. Tables 6 to 8 examine the predictive power of RA_M while Tables 9 to 11 refer to RA_A. Tables 6 and 9 apply value-weighted Fama-MacBeth-regressions in order to put lower weight on small caps; in Tables 7 and 10 all explanatory variables are winsorized at 1% and 99% to examine whether the findings are merely driven by extreme outliers; in Tables 8 and 11 we also include skewness, coskewness, idiosyncratic skewness, and downside beta as additional control variables. The regression coefficients for RA_M and RA_A remain significantly positive in all specifications.

Table 6. Monthly Recency Adjustment in Value-Weighted Fama-MacBeth-Regressions
This table reports value-weighted Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1 of the main paper. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	0.9438	1.9689	1.6006	1.7029	2.3146	2.3220	2.1618	1.9956	2.0070
	(6.01)	(3.69)	(3.20)	(3.27)	(4.36)	(4.37)	(3.96)	(3.46)	(3.50)
RA_M	0.0911	0.0997	0.1115	0.1149	0.1178	0.1180	0.1177	0.1200	0.1204
	(5.88)	(8.59)	(9.94)	(10.76)	(11.40)	(11.38)	(11.43)	(11.74)	(11.73)
BETA		0.1251	0.0155	0.0244	0.1166	0.1208	0.1089	0.1016	0.0999
		(0.88)	(0.12)	(0.18)	(0.87)	(0.90)	(0.82)	(0.76)	(0.76)
ln(MV)		-0.0538	-0.0444	-0.0465	-0.0691	-0.0692	-0.0633	-0.0579	-0.0574
		(-2.25)	(-2.01)	(-2.04)	(-3.08)	(-3.09)	(-2.80)	(-2.49)	(-2.48)
BM		0.0727	0.1632	0.1411	0.1357	0.1330	0.1332	0.1244	0.1228
		(1.18)	(3.04)	(2.58)	(2.49)	(2.44)	(2.51)	(2.34)	(2.32)
MOM			0.0093	0.0095	0.0100	0.0100	0.0092	0.0098	0.0098
			(5.49)	(5.33)	(5.87)	(5.86)	(4.70)	(5.21)	(5.24)
ltREV			-0.0008	-0.0009	-0.0008	-0.0008	-0.0008	-0.0006	-0.0005
			(-1.29)	(-1.40)	(-1.45)	(-1.45)	(-1.41)	(-1.22)	(-1.19)
REV				-0.0422	-0.0487	-0.0486	-0.0488	-0.0498	-0.0518
				(-10.07)	(-10.32)	(-10.29)	(-10.64)	(-10.99)	(-10.90)
IVOL					-0.3968	-0.4443	-0.4355	-0.4505	-0.4600
					(-0.79)	(-0.88)	(-0.87)	(-0.94)	(-0.98)
MAX					0.0248	0.0242	0.0230	0.0234	0.0098
					(1.46)	(1.43)	(1.36)	(1.41)	(0.54)
MIN					0.0717	0.0727	0.0723	0.0765	0.0642
					(4.01)	(4.07)	(4.05)	(4.36)	(3.28)
ILLIQ						0.0126	0.0117	0.0137	0.0146
						(0.92)	(0.83)	(0.96)	(1.04)
RR							0.2428	0.2481	0.2509
							(1.74)	(1.84)	(1.84)
TK								-1.9488	-1.7901
								(-1.08)	(-1.02)
ST									0.0325
									(1.59)

Table 7. Monthly Recency Adjustment in Fama-MacBeth-Regressions – Winsorized
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1 of the main paper and are all winsorized at 1% and 99%. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.2833	3.4014	3.1176	2.9251	3.7441	3.3820	3.2625	2.9161	2.8271
	(6.09)	(4.16)	(4.35)	(3.81)	(5.95)	(5.49)	(5.32)	(4.86)	(4.65)
RA_M	0.1678	0.1910	0.2016	0.2075	0.2116	0.2110	0.2100	0.2103	0.2099
	(18.32)	(21.15)	(21.79)	(22.50)	(22.63)	(22.69)	(22.59)	(22.58)	(22.57)
BETA		-0.0193	-0.0750	-0.1041	0.0140	0.0707	0.0829	0.0565	0.0628
		(-0.16)	(-0.69)	(-0.91)	(0.13)	(0.65)	(0.76)	(0.54)	(0.61)
ln(MV)		-0.1270	-0.1266	-0.1099	-0.1423	-0.1216	-0.1291	-0.1199	-0.1173
		(-3.12)	(-3.59)	(-2.92)	(-4.60)	(-4.03)	(-4.36)	(-4.17)	(-4.08)
BM		0.1337	0.2485	0.1694	0.1672	0.1452	0.1462	0.1386	0.1379
		(2.76)	(5.41)	(3.99)	(4.01)	(3.63)	(3.68)	(3.49)	(3.48)
MOM			0.0098	0.0091	0.0092	0.0091	0.0063	0.0076	0.0077
			(5.02)	(4.38)	(4.48)	(4.44)	(2.83)	(3.83)	(3.95)
ltREV			-0.0010	-0.0014	-0.0014	-0.0013	-0.0013	-0.0006	-0.0005
			(-1.92)	(-2.36)	(-2.62)	(-2.52)	(-2.51)	(-1.24)	(-1.08)
REV				-0.0717	-0.0738	-0.0738	-0.0754	-0.0749	-0.0710
				(-16.30)	(-16.52)	(-16.40)	(-16.70)	(-16.65)	(-15.36)
IVOL					0.3341	-0.1075	-0.0974	-0.1200	-0.0685
					(0.93)	(-0.29)	(-0.27)	(-0.34)	(-0.19)
MAX					-0.0331	-0.0301	-0.0307	-0.0301	-0.0116
					(-2.86)	(-2.63)	(-2.67)	(-2.64)	(-0.95)
MIN					0.0633	0.0676	0.0687	0.0706	0.0898
					(5.35)	(5.72)	(5.83)	(5.98)	(6.25)
ILLIQ						0.0422	0.0421	0.0423	0.0420
						(4.38)	(4.36)	(4.44)	(4.39)
RR							0.5695	0.5681	0.5770
							(5.68)	(5.84)	(5.70)
TK								-4.0777	-4.2001
								(-2.47)	(-2.52)
ST									-0.0528
									(-3.19)

Table 8. Monthly Recency Adjustment in Fama-MacBeth-Regressions – Additional Controls
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. SKEW is the return skewness of daily returns in the previous month. COSKEW is coskewness following Harvey and Siddique (2000) based on the daily returns of the previous month. ISKEW is the idiosyncratic return skewness of the previous month with respect to the three Fama-French-factors. DBETA is the downside market beta based on daily returns of the previous year as introduced by Ang et al. (2006a). The other explanatory variables are described in Table 1 of the main paper. TK is estimated based on daily data of the previous month instead of using monthly data from the previous five years. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.3500	3.8753	3.6733	3.2699	3.7365	3.5760	3.4685	3.2213	3.0736
	(7.61)	(4.71)	(5.06)	(4.26)	(5.98)	(5.73)	(5.59)	(5.29)	(4.96)
RA_M	0.1602	0.1761	0.1847	0.1898	0.1944	0.1933	0.1923	0.1931	0.1933
	(20.65)	(21.65)	(22.22)	(22.97)	(23.22)	(23.37)	(23.34)	(23.26)	(23.26)
BETA		0.0506	-0.0425	-0.1051	-0.0101	0.0260	0.0375	0.0033	0.0191
		(0.35)	(-0.32)	(-0.75)	(-0.07)	(0.19)	(0.27)	(0.02)	(0.14)
ln(MV)		-0.1483	-0.1479	-0.1240	-0.1407	-0.1317	-0.1429	-0.1352	-0.1305
		(-3.64)	(-4.13)	(-3.29)	(-4.58)	(-4.34)	(-4.81)	(-4.69)	(-4.51)
BM		0.0718	0.1221	0.0804	0.0835	0.0785	0.0817	0.0794	0.0785
		(2.40)	(4.29)	(3.01)	(3.18)	(3.03)	(3.19)	(2.99)	(2.98)
MOM			0.0078	0.0076	0.0077	0.0078	0.0052	0.0061	0.0062
			(4.14)	(3.82)	(3.88)	(3.95)	(2.43)	(3.09)	(3.15)
ltREV			-0.0008	-0.0011	-0.0010	-0.0009	-0.0009	-0.0006	-0.0005
			(-2.41)	(-2.55)	(-2.74)	(-2.66)	(-2.64)	(-1.55)	(-1.45)
REV				-0.0669	-0.0705	-0.0697	-0.0714	-0.0712	-0.0661
				(-16.80)	(-17.07)	(-17.01)	(-17.54)	(-17.34)	(-15.45)
IVOL					0.3155	-0.0537	-0.0007	-0.0134	0.1899
					(0.86)	(-0.15)	(-0.00)	(-0.04)	(0.53)
MAX					-0.0223	-0.0208	-0.0217	-0.0214	-0.0028
					(-1.37)	(-1.27)	(-1.33)	(-1.34)	(-0.18)
MIN					0.0554	0.0467	0.0494	0.0521	0.0793
					(3.26)	(2.78)	(2.95)	(3.17)	(4.83)
ILLIQ						0.0209	0.0208	0.0209	0.0203
						(3.19)	(3.15)	(3.17)	(3.15)
RR							0.6466	0.6365	0.6392
							(6.49)	(6.60)	(6.52)
TK								-3.0522	-3.1861
								(-1.98)	(-2.06)
ST									-0.0779
									(-4.80)
SKEW	-0.2078	-0.2446	-0.2314	-0.0099	0.0311	0.0458	0.0415	0.0306	0.0506
	(-5.69)	(-6.64)	(-6.70)	(-0.31)	(0.57)	(0.82)	(0.75)	(0.58)	(0.97)
CSKW	0.1842	0.1649	0.1921	0.0923	0.0523	0.0517	0.0545	0.0538	0.0242
	(2.66)	(3.08)	(3.49)	(1.81)	(0.99)	(0.96)	(1.01)	(1.00)	(0.44)
ISKW	0.0346	0.0082	-0.0051	0.0712	0.0627	0.0659	0.0667	0.0710	0.0977
	(1.00)	(0.27)	(-0.18)	(2.60)	(2.30)	(2.46)	(2.46)	(2.67)	(3.37)
DBETA	-0.0426	-0.0429	-0.0019	0.0292	0.0241	0.0125	0.0180	0.0264	0.0174
	(-0.64)	(-0.75)	(-0.04)	(0.52)	(0.38)	(0.20)	(0.29)	(0.43)	(0.29)

Table 9. Annual Recency Adjustment in Value-Weighted Fama-MacBeth-Regressions
This table reports value-weighted Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1 of the main paper. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	0.8969	1.9252	1.5342	1.5716	2.3133	2.3279	2.1339	1.9277	1.9312
	(5.02)	(3.52)	(2.97)	(3.05)	(4.39)	(4.41)	(3.97)	(3.36)	(3.38)
RA_A	0.0347	0.0391	0.0357	0.0195	0.0176	0.0175	0.0184	0.0180	0.0183
	(6.30)	(9.02)	(8.30)	(3.91)	(3.72)	(3.68)	(3.77)	(3.74)	(3.79)
BETA		0.0395	-0.0815	-0.0659	0.0463	0.0499	0.0389	0.0354	0.0350
		(0.25)	(-0.59)	(-0.47)	(0.34)	(0.36)	(0.28)	(0.26)	(0.26)
ln(MV)		-0.0503	-0.0394	-0.0396	-0.0678	-0.0682	-0.0644	-0.0577	-0.0569
		(-2.05)	(-1.73)	(-1.77)	(-3.08)	(-3.10)	(-2.90)	(-2.50)	(-2.47)
BM		0.0702	0.1556	0.1431	0.1384	0.1360	0.1378	0.1279	0.1265
		(1.11)	(2.84)	(2.63)	(2.55)	(2.50)	(2.60)	(2.42)	(2.41)
MOM			0.0084	0.0086	0.0091	0.0091	0.0078	0.0086	0.0086
			(4.60)	(4.78)	(5.18)	(5.16)	(3.91)	(4.43)	(4.43)
ltREV			-0.0008	-0.0008	-0.0008	-0.0008	-0.0007	-0.0005	-0.0004
			(-1.22)	(-1.32)	(-1.32)	(-1.31)	(-1.27)	(-0.97)	(-0.92)
REV				-0.0333	-0.0406	-0.0406	-0.0412	-0.0422	-0.0439
				(-6.69)	(-7.68)	(-7.66)	(-8.05)	(-8.43)	(-8.30)
IVOL					-0.6291	-0.6784	-0.6518	-0.6999	-0.7036
					(-1.20)	(-1.29)	(-1.25)	(-1.41)	(-1.44)
MAX					0.0252	0.0246	0.0236	0.0245	0.0123
					(1.44)	(1.41)	(1.36)	(1.44)	(0.67)
MIN					0.0629	0.0637	0.0627	0.0660	0.0551
					(3.44)	(3.49)	(3.44)	(3.68)	(2.77)
ILLIQ						0.0099	0.0093	0.0116	0.0127
						(0.78)	(0.71)	(0.87)	(0.97)
RR							0.3285	0.3286	0.3280
							(2.46)	(2.61)	(2.58)
TK								-2.4133	-2.2898
								(-1.30)	(-1.26)
ST									0.0290
									(1.43)

Table 10. Annual Recency Adjustment in Fama-MacBeth-Regressions – Winsorized
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1 of the main paper and are all winsorized at 1% and 99%. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.1822	3.0996	2.8029	2.7018	3.7260	3.3467	3.1654	2.8050	2.7303
	(5.04)	(3.60)	(3.66)	(3.44)	(6.00)	(5.49)	(5.26)	(4.75)	(4.58)
RA_A	0.0472	0.0466	0.0431	0.0133	0.0118	0.0126	0.0149	0.0151	0.0152
	(9.47)	(12.20)	(11.05)	(4.04)	(3.76)	(3.95)	(4.59)	(4.61)	(4.59)
BETA		-0.0747	-0.1406	-0.1218	0.0056	0.0617	0.0798	0.0525	0.0590
		(-0.56)	(-1.19)	(-1.03)	(0.05)	(0.54)	(0.70)	(0.48)	(0.54)
ln(MV)		-0.1106	-0.1081	-0.0994	-0.1416	-0.1197	-0.1304	-0.1207	-0.1185
		(-2.59)	(-2.87)	(-2.60)	(-4.62)	(-4.01)	(-4.44)	(-4.21)	(-4.15)
BM		0.1275	0.2275	0.1733	0.1725	0.1495	0.1512	0.1438	0.1433
		(2.58)	(5.03)	(4.05)	(4.12)	(3.72)	(3.79)	(3.62)	(3.61)
MOM			0.0076	0.0081	0.0079	0.0077	0.0042	0.0055	0.0056
			(3.78)	(3.75)	(3.71)	(3.60)	(1.79)	(2.57)	(2.66)
ltREV			-0.0011	-0.0013	-0.0013	-0.0012	-0.0012	-0.0005	-0.0004
			(-1.97)	(-2.26)	(-2.48)	(-2.36)	(-2.35)	(-1.06)	(-0.94)
REV				-0.0653	-0.0669	-0.0665	-0.0681	-0.0674	-0.0642
				(-15.32)	(-15.42)	(-15.23)	(-15.56)	(-15.64)	(-14.07)
IVOL					-0.0240	-0.4637	-0.4209	-0.4440	-0.4118
					(-0.07)	(-1.27)	(-1.15)	(-1.24)	(-1.13)
MAX					-0.0296	-0.0269	-0.0275	-0.0270	-0.0128
					(-2.53)	(-2.30)	(-2.36)	(-2.33)	(-1.05)
MIN					0.0459	0.0501	0.0522	0.0542	0.0690
					(3.85)	(4.26)	(4.45)	(4.62)	(4.82)
ILLIQ						0.0417	0.0417	0.0419	0.0419
						(4.33)	(4.33)	(4.41)	(4.38)
RR							0.7505	0.7521	0.7614
							(7.85)	(8.12)	(7.92)
TK								-4.1961	-4.2933
								(-2.52)	(-2.56)
ST									-0.0425
									(-2.51)

Table 11. Annual Recency Adjustment in Fama-MacBeth-Regressions – Additional Controls
This table reports Fama-MacBeth-regression estimates for the sample period from January 1931 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. SKEW is the return skewness of daily returns in the previous month. COSKEW is coskewness following Harvey and Siddique (2000) based on the daily returns of the previous month. ISKEW is the idiosyncratic return skewness of the previous month with respect to the three Fama-French-factors. DBETA is the downside market beta based on daily returns of the previous year as introduced by Ang et al. (2006a). The other explanatory variables are described in Table 1 of the main paper. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	1.2549	3.5634	3.3543	3.1247	3.7349	3.5647	3.4012	3.1265	3.0004
	(6.77)	(4.16)	(4.37)	(4.00)	(6.04)	(5.78)	(5.60)	(5.23)	(4.93)
RA_A	0.0440	0.0407	0.0378	0.0104	0.0086	0.0091	0.0114	0.0116	0.0117
	(10.18)	(11.90)	(10.86)	(3.40)	(2.90)	(3.05)	(3.76)	(3.82)	(3.82)
BETA		-0.0379	-0.1294	-0.1080	-0.0237	0.0095	0.0242	-0.0095	0.0075
		(-0.25)	(-0.96)	(-0.77)	(-0.17)	(0.07)	(0.17)	(-0.07)	(0.05)
ln(MV)		-0.1320	-0.1302	-0.1171	-0.1405	-0.1310	-0.1445	-0.1360	-0.1319
		(-3.11)	(-3.44)	(-3.06)	(-4.59)	(-4.34)	(-4.89)	(-4.73)	(-4.57)
BM		0.0671	0.1104	0.0808	0.0857	0.0806	0.0846	0.0825	0.0818
		(2.20)	(3.93)	(3.01)	(3.24)	(3.09)	(3.29)	(3.10)	(3.09)
MOM			0.0062	0.0069	0.0068	0.0069	0.0036	0.0046	0.0046
			(3.25)	(3.38)	(3.30)	(3.31)	(1.63)	(2.17)	(2.22)
ltREV			-0.0008	-0.0010	-0.0009	-0.0009	-0.0008	-0.0004	-0.0004
			(-2.33)	(-2.43)	(-2.54)	(-2.44)	(-2.40)	(-1.15)	(-1.08)
REV				-0.0617	-0.0662	-0.0652	-0.0666	-0.0663	-0.0620
				(-15.89)	(-16.02)	(-15.85)	(-16.40)	(-16.40)	(-14.31)
IVOL					0.0044	-0.3566	-0.2796	-0.2932	-0.1186
					(0.01)	(-0.99)	(-0.77)	(-0.83)	(-0.33)
MAX					-0.0134	-0.0123	-0.0132	-0.0126	0.0033
					(-0.84)	(-0.76)	(-0.82)	(-0.80)	(0.21)
MIN					0.0465	0.0373	0.0407	0.0440	0.0676
					(2.72)	(2.22)	(2.43)	(2.68)	(4.12)
ILLIQ						0.0202	0.0201	0.0202	0.0198
						(3.10)	(3.08)	(3.11)	(3.09)
RR							0.7942	0.7882	0.7893
							(8.00)	(8.19)	(8.14)
TK								-3.3154	-3.4109
								(-2.12)	(-2.17)
ST									-0.0662
									(-3.89)
SKEW	-0.1767	-0.2149	-0.2057	-0.0463	-0.0080	0.0079	0.0034	-0.0094	0.0074
	(-4.99)	(-5.92)	(-6.28)	(-1.41)	(-0.15)	(0.15)	(0.06)	(-0.19)	(0.15)
CSKW	0.1497	0.1294	0.1538	0.1168	0.0849	0.0842	0.0854	0.0854	0.0611
	(2.37)	(2.53)	(3.00)	(2.24)	(1.51)	(1.50)	(1.51)	(1.54)	(1.08)
ISKW	0.0647	0.0432	0.0295	0.0802	0.0723	0.0766	0.0775	0.0818	0.1059
	(1.88)	(1.39)	(0.98)	(2.77)	(2.54)	(2.73)	(2.73)	(2.91)	(3.50)
DBETA	-0.0623	-0.0048	0.0296	0.0268	0.0299	0.0205	0.0242	0.0337	0.0249
	(-0.84)	(-0.09)	(0.58)	(0.51)	(0.49)	(0.34)	(0.40)	(0.57)	(0.42)

4. Subperiod Analysis

In this section, we examine the return predictability associated with RA_M and RA_A across time. Table 12 shows that the decile return spreads are highly significant and larger than 1% for both halves of the sample period. This holds for both RA_M and RA_A, for both equally- and value-weighted portfolios, and for both raw and Fama-French-Carhart-adjusted returns. Table 13 shows that the predictability also remains positive in both subsamples if we control for other cross-sectional return determinants in Fama-MacBeth-regressions.

Figure 1 graphically displays long-short portfolio returns based on RA_M and RA_A from 1931 to 2016. For comparability reasons, the long-short returns for recency adjustment are based on the difference between extreme terciles instead of deciles and based on value-weighted portfolios. Beside the investment charts for RA_M and RA_A, Figure 1a also shows the development of the factors MKT, SMB, HML, and WML (all obtained from Kenneth R. French's homepage). Figure 1b displays the same time series, but the long-short returns are all standardized to have the same monthly volatility as the market excess return MKT. The graph shows, that the return premiums associated with RA_M have a similar magnitude than the premiums of MKT, HML, and WML. The long-short returns based on RA_A are even higher. In addition, Figure 1 graphically supports the previous findings: the return patterns associated with RA_M and RA_A are not restricted to particular subperiods.

Table 12. Portfolio Sorts Based on Recency Adjustment – Subperiods
This table reports monthly decile portfolio sorts based on monthly recency adjustment, RA_M, in Panel A and annual recency adjustment, RA_A, in Panel B. RA_M is based on the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. Subsequent portfolio returns are provided for the first half of the sample period from January 1931 to December 1973 and for the second half from January 1974 to December 2016. They are based on equally- or value-weighted raw or FFC-adjusted returns. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns and alphas are stated in %.

Panel A: Portfolio Sorts Based on RA_M

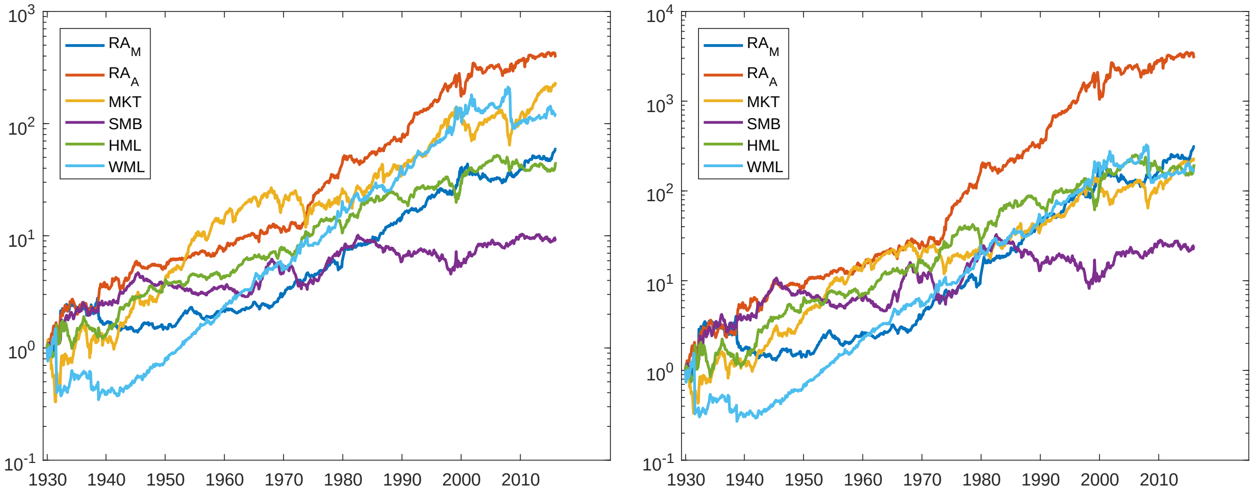
	1926-1973				1974-2016			
	equally-weighted		value-weighted		equally-weighted		value-weighted	
	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}
low	0.19	-1.14	0.31	-0.86	0.02	-1.19	0.15	-0.89
2	0.89	-0.29	0.83	-0.14	0.97	-0.21	0.62	-0.39
3	1.17	-0.01	0.88	-0.10	1.20	0.04	0.78	-0.22
4	1.17	0.08	0.93	0.05	1.28	0.15	0.91	-0.06
5	1.34	0.27	1.09	0.24	1.38	0.25	1.02	0.06
6	1.18	0.06	0.97	0.06	1.41	0.27	0.99	0.03
7	1.40	0.21	0.96	-0.02	1.52	0.38	1.15	0.20
8	1.37	0.16	1.11	0.10	1.70	0.54	1.22	0.30
9	1.72	0.33	1.13	0.02	1.86	0.70	1.29	0.32
high	2.10	0.69	1.42	0.17	2.41	1.26	1.65	0.57
10-1	1.91	1.83	1.11	1.04	2.39	2.45	1.50	1.46
t(10-1)	(7.57)	(7.53)	(3.64)	(3.42)	(10.62)	(9.31)	(6.38)	(5.81)

Panel B: Portfolio Sorts Based on RA_A

	1926-1973				1974-2016			
	equally-weighted		value-weighted		equally-weighted		value-weighted	
	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}
low	0.34	-1.01	0.48	-0.69	0.59	-0.68	0.62	-0.49
2	0.69	-0.47	0.69	-0.31	0.98	-0.22	0.67	-0.34
3	0.95	-0.24	0.81	-0.19	1.11	-0.08	0.71	-0.31
4	1.15	0.04	1.09	0.10	1.23	0.08	0.83	-0.21
5	1.14	0.02	0.87	-0.11	1.29	0.15	0.93	-0.04
6	1.28	0.16	0.97	0.03	1.36	0.25	1.18	0.24
7	1.40	0.20	1.16	0.20	1.52	0.40	1.22	0.24
8	1.51	0.33	1.25	0.28	1.63	0.52	1.30	0.31
9	1.73	0.48	1.30	0.19	1.78	0.65	1.62	0.60
high	2.31	0.85	1.66	0.53	2.26	1.12	1.64	0.55
10-1	1.97	1.86	1.18	1.22	1.66	1.79	1.02	1.04
t(10-1)	(6.06)	(6.31)	(4.14)	(4.31)	(7.24)	(6.24)	(3.96)	(3.74)

Table 13. Recency Adjustment in Fama-MacBeth-Regressions – Subperiods
This table reports Fama-MacBeth-regression estimates based on monthly data. The dependent variable is the stock return of the subsequent month. In the first two columns, RA refers to a monthly formation period, while RA refers to an annual formation period in the last two columns. In the first and the third column, the sample period is January 1931 to December 1973. In the second and the fourth column, the sample period is January 1974 to December 2016. The explanatory variables are described in Table 1 of the main Paper. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	RA_M		RA_A	
	1926-1973	1974-2016	1926-1973	1974-2016
intercept	3.0202	3.2186	2.8706	3.1489
	(3.08)	(4.18)	(3.00)	(4.10)
RA_A	0.2232	0.1629	0.0127	0.0113
	(20.86)	(15.43)	(2.51)	(3.44)
BETA	-0.0520	0.1079	-0.0320	0.0789
	(-0.35)	(0.74)	(-0.20)	(0.53)
ln(MV)	-0.1351	-0.1276	-0.1340	-0.1289
	(-2.86)	(-3.63)	(-2.85)	(-3.65)
BM	0.0468	0.1052	0.0480	0.1116
	(1.52)	(2.54)	(1.57)	(2.67)
MOM	0.0092	0.0035	0.0071	0.0024
	(2.61)	(2.51)	(1.87)	(1.71)
ltREV	-0.0006	-0.0004	-0.0005	-0.0003
	(-0.91)	(-1.45)	(-0.67)	(-1.17)
REV	-0.0775	-0.0565	-0.0733	-0.0508
	(-12.48)	(-10.55)	(-11.53)	(-10.07)
IVOL	0.6532	-0.3129	0.1958	-0.4900
	(1.10)	(-0.83)	(0.32)	(-1.29)
MAX	-0.0240	0.0382	-0.0212	0.0392
	(-1.32)	(2.38)	(-1.19)	(2.44)
MIN	0.0836	0.1003	0.0522	0.0953
	(3.78)	(7.72)	(2.36)	(7.05)
ILLIQ	0.0274	0.0134	0.0261	0.0138
	(2.20)	(4.39)	(2.10)	(4.50)
RR	0.4457	0.8189	0.6244	0.9418
	(2.85)	(8.53)	(4.01)	(10.37)
TK	-3.2608	-3.6310	-3.3856	-3.8322
	(-1.43)	(-1.67)	(-1.49)	(-1.72)
ST	-0.0642	-0.0823	-0.0468	-0.0824
	(-2.95)	(-4.07)	(-2.06)	(-3.98)



(a) Portfolio Returns **(b)** Standardized Portfolio Returns

Figure 1. This figure shows the returns of long-short portfolios based on recency adjustment. The long-short portfolios are readjusted every month and are calculated as the subsequent value-weighted return difference between high and low tercile. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. For comparison, the figure also shows return series for the Fama-French-Carhart-factors MKT, SMB, HML, and WML. Subfigure (a) presents unadjusted value-weighted return series. In subfigure (b), all time series are scaled such that all series have the same monthly return volatility as MKT. The sample period is January 1931 to December 2016.

5. Further Robustness Tests

Table 14 further supports a behavioral explanation for the return predictability associated with recency adjustment. The decile portfolio sorts cover all NASDAQ stocks from January 1987 to December 2016 and show that the return spreads are largest among those stocks that have a low dollar volume per trade in the previous month. Hence, in line with behavioral arguments, the return predictability is largest for stocks with comparably many small and private investors.

Table 15 presents portfolio sorts for a sample period from January 1996 to December 2016 based on RA_M in Panel A and RA_A in Panel B. For each decile portfolio, average values of VS_{BH} (Bali and Hovakimian, 2009), VS_{CW} (Cremers and Weinbaum, 2010), and SMIRK (Xing et al., 2010) are presented. These metrics are based on the difference between option-implied call and put volatilities and thereby implicitly reflect option trader demand in call versus put options.[3] High [low] values of these three measures indicate comparably high call [put] implied volatilities, high call [put] prices, a high demand for calls [puts], and hence an optimistic [pessimistic] return expectation of informed option traders. These arguments follow the demand-based option pricing framework of Garleanu et al. (2009) and can be used to decide whether sophisticated option market participants consider stocks as over- or undervalued. According to Table 15, stocks with high values of recency adjustment indeed have higher option measures VS_{BH}, VS_{CW}, and SMIRK indicating that high-RA stocks are correctly considered as undervalued by sophisticated option market participants and vice versa. This supports a mispricing explanation for the return predictability of recency adjustment.

Tables 16 to 18 examine the decile portfolio returns after controlling for each of the variables introduced in Table 1 of the main paper. These Tables are equivalent to Table 8 of

[3]More specifically, VS_{BH} is the implied volatility spread between near-the-money options which have an absolute natural log moneyness level lower than 0.1. Based on that, VS_{BH} equals the difference between average near-the-money call implied volatility and average near-the-money put implied volatility. VS_{CW} is based on a stock's call-put-option-pairs where call and put have identical strike prices. VS_{CW} is calculated as the open interest-weighted average of the resulting call-put volatility spreads. SMIRK is calculated as the difference between at-the-money call implied volatility and out-of-the-money put implied volatility. The at-the-money call is identified as the call option that has the lowest deviation from a moneyness of one. The out-of-the-money put option is defined as the put option with a moneyness closest to 0.95 but below 0.95. The corresponding option data is sourced from Optionmetrics.

the main paper. Table 16 presents the same conditional double sorts using Fama-French-Carhart-adjusted equally-weighted returns, Table 17 presents equally-weighted raw returns, and Table 18 presents value-weighted raw returns.

Tables 19 to 22 examine whether the return predictability of RA_M and RA_A is particularly strong if limits to arbitrage are more severe. The analyses mainly follow Table 6 in the main paper. Table 19 presents the same conditional double sorts using Fama-French-Carhart-adjusted equally-weighted returns, Table 20 presents equally-weighted raw returns, and Table 21 value-weighted raw returns. In all specifications, the decile return spreads associated with RA_M and RA_A are higher among stocks with high illiquidity, high idiosyncratic volatility, and high absolute maximum daily return. This line of argument is also supported by Fama-MacBeth-regressions in Table 22: the interaction terms of recency adjustment and limits to arbitrage proxy are significantly positive supporting the hypothesis that the recency effects are stronger for stocks with high limits to arbitrage.

Table 23 presents decile portfolio sorts given that the estimation of recency adjustment is based on different time horizons. The positive relation between recency adjustment and subsequent returns is significant for all of the four formation periods (6, 12, 36, and 60 months). The return spreads, are strongest for an annual formation period (RA_{12M}) and gradually decrease for longer horizons. This pattern is also detectable in Fama-MacBeth-regressions provided in Table 24. The influence of recency adjustment becomes less important for longer horizons; while it is highly significant for an annual formation period, the coefficient's magnitude strongly decreases for a formation period of five years.

Table 25 supports the evidence from Fama-MacBeth-regressions provided in the main paper (see Table 9). Accordingly, RA_M and RA_A also significantly predict subsequent returns if their estimation is based on correlation or rank correlation instead of covariance. Table 25 shows that (rank) correlation-based versions of RA_M and RA_A generate strong return spreads in decile portfolio sorts, too. The difference portfolio is statistically significant in all specifications and yields at least 0.74% on a monthly basis.

Table 14. Recency Effect Dependence on Trade Size
This table reports monthly subsequent returns from portfolio double sorts. First, each stock is allocated to a top or bottom portfolio based on its average trading volume per trade in the previous month. Second, within each portfolio, each stock is allocated to a decile portfolio based on RA_M or RA_A. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. Panel A refers to equally-weighted FFC-adjusted returns, Panel B to value-weighted FFC-adjusted returns, Panel C to equally-weighted raw returns, and Panel D to value-weighted raw returns. The analysis covers all NASDAQ stocks from January 1987 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Subsequent returns are stated in %.

	Panel A: Equally-Weighted FFC-Adj. Returns				Panel B: Value-Weighted FFC-Adj. Returns			
	High Trade Size		Low Trade Size		High Trade Size		Low Trade Size	
	RA_M	RA_A	RA_M	RA_A	RA_M	RA_A	RA_M	RA_A
low	-1.29	-0.20	-2.38	-1.41	-1.36	-0.34	-2.90	-1.39
2	-0.36	0.14	-1.07	0.02	-0.29	0.10	-1.40	-0.33
3	0.22	0.14	0.06	0.28	0.25	-0.11	-0.20	0.29
4	0.50	0.32	0.27	0.29	0.33	0.21	-0.14	-0.32
5	0.41	0.51	0.44	0.38	0.48	0.28	0.19	-0.40
6	0.84	0.58	1.04	0.82	0.65	0.35	0.58	0.58
7	0.81	0.84	1.22	0.87	0.46	0.82	0.79	0.29
8	0.59	0.52	1.56	1.23	0.50	0.37	1.15	0.15
9	0.94	0.65	2.48	1.63	0.69	0.18	1.38	0.91
high	1.62	0.79	3.21	2.71	1.22	0.54	1.83	1.31
10-1	2.91	0.99	5.58	4.12	2.58	0.88	4.73	2.70
t(10-1)	(5.80)	(3.18)	(7.49)	(6.27)	(4.65)	(2.37)	(4.43)	(4.70)

	Panel C: Equally-Weighted Raw Returns				Panel D: Value-Weighted Raw Returns			
	High Trade Size		Low Trade Size		High Trade Size		Low Trade Size	
	RA_M	RA_A	RA_M	RA_A	RA_M	RA_A	RA_M	RA_A
low	-0.38	0.84	-1.64	-0.64	-0.48	0.69	-2.11	-0.53
2	0.51	1.07	-0.44	0.76	0.56	1.05	-0.68	0.38
3	1.01	1.05	0.79	0.97	1.08	0.84	0.44	1.03
4	1.29	1.15	0.97	0.96	1.17	1.10	0.60	0.40
5	1.26	1.33	1.07	0.97	1.27	1.07	0.90	0.32
6	1.66	1.38	1.68	1.46	1.53	1.15	1.26	1.18
7	1.67	1.60	1.84	1.55	1.34	1.52	1.46	0.97
8	1.48	1.31	2.24	1.78	1.39	1.23	1.75	0.87
9	1.81	1.43	3.09	2.29	1.58	0.95	2.14	1.44
high	2.45	1.61	3.76	3.28	2.07	1.41	2.30	1.87
10-1	2.83	0.76	5.39	3.92	2.56	0.72	4.41	2.40
t(10-1)	(6.36)	(2.36)	(8.80)	(6.54)	(5.07)	(1.76)	(5.68)	(4.83)

Table 15. Portfolio Sorts Including Option-Based Measures of Informed Trading
This table reports monthly decile portfolio sorts based on RA_M in Panel A and RA_A in Panel B for the sample period from January 1996 to December 2016. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The table presents portfolio averages for RA, subsequent monthly returns R, VS_{BH}, VS_{CW}, and SMIRK. VS_{BH} is the at-the-money option-implied volatility spread following Bali and Hovakimian (2009). VS_{CW} is the open-interest-weighted option-implied volatility spread following Cremers and Weinbaum (2010). SMIRK is the option-implied volatility smirk following Xing et al. (2010). These three metrics are based on option data of the last day of month and the metrics are signed, that is, higher values indicate a more positive opinion of option investors. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Panel A: Portfolio Sorts Based on RA_M					Panel B: Portfolio Sorts Based on RA_A				
	RA_M	R	VS_{BH}	VS_{CW}	SMIRK	RA_A	R	VS_{BH}	VS_{CW}	SMIRK
low	-8.35	-0.08	-0.0182	-0.0194	-0.0628	-27.57	0.76	-0.0149	-0.0158	-0.0624
2	-3.59	0.77	-0.0131	-0.0128	-0.0577	-12.07	0.98	-0.0108	-0.0098	-0.0556
3	-2.16	1.02	-0.0110	-0.0098	-0.0542	-7.16	1.04	-0.0087	-0.0070	-0.0533
4	-1.23	1.05	-0.0100	-0.0080	-0.0542	-3.88	1.11	-0.0090	-0.0071	-0.0528
5	-0.49	1.14	-0.0090	-0.0069	-0.0530	-1.22	1.10	-0.0087	-0.0065	-0.0519
6	0.21	1.15	-0.0081	-0.0063	-0.0523	1.28	1.05	-0.0077	-0.0058	-0.0511
7	0.95	1.34	-0.0059	-0.0038	-0.0505	3.96	1.22	-0.0066	-0.0047	-0.0512
8	1.86	1.41	-0.0053	-0.0034	-0.0503	7.28	1.21	-0.0071	-0.0054	-0.0515
9	3.25	1.69	-0.0043	-0.0026	-0.0495	12.28	1.40	-0.0059	-0.0047	-0.0513
high	7.97	2.13	-0.0042	-0.0028	-0.0503	27.62	1.71	-0.0083	-0.0082	-0.0544
10-1	16.32	2.21	0.0139	0.0166	0.0125	55.19	0.95	0.0066	0.0076	0.0081
t(10-1)		(5.89)	(7.85)	(7.80)	(8.63)		(3.35)	(3.79)	(3.79)	(3.87)

Table 16. Double Sorts based on Recency Adjustment – Equally-Weighted FFC-Adjusted Returns

This table reports monthly FFC-adjusted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a decile portfolio based on one of the control variables BETA, ln(MV), BM, MOM, ltREV, REV, IVOL, MAX, MIN, ILLIQ, RR, TK, or ST as introduced in Table 1. Second, within each decile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A and RA_A in Panel B. RA_M is the recency adjustment for the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. For each of the resulting 100 portfolios, the equally-weighted return is calculated. These 100 portfolio returns are then aggregated across the first sorting criterion, that is, the reported RA-decile returns are computed as the average return among the ten corresponding portfolios sorted by one of the control variables. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

Panel A: Monthly Recency Adjustment RA_M

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	-1.06	-1.14	-1.16	-1.18	-1.15	-1.07	-0.91	-0.84	-1.05	-1.12	-1.08	-1.23	-0.94
2	-0.18	-0.34	-0.33	-0.33	-0.28	-0.27	-0.40	-0.37	-0.33	-0.35	-0.28	-0.33	-0.33
3	0.03	-0.07	-0.02	-0.08	-0.02	-0.08	-0.19	-0.21	-0.12	-0.05	-0.07	-0.01	-0.09
4	0.04	0.10	0.07	0.10	0.06	0.06	0.00	0.02	0.10	0.12	0.13	0.15	0.05
5	0.18	0.23	0.19	0.21	0.19	0.23	0.11	0.10	0.14	0.22	0.17	0.25	0.11
6	0.20	0.35	0.22	0.28	0.28	0.17	0.27	0.21	0.33	0.27	0.26	0.27	0.26
7	0.31	0.35	0.39	0.33	0.38	0.28	0.40	0.30	0.37	0.39	0.31	0.33	0.28
8	0.31	0.48	0.42	0.40	0.39	0.43	0.55	0.43	0.49	0.40	0.43	0.41	0.40
9	0.54	0.61	0.58	0.57	0.56	0.56	0.60	0.55	0.59	0.62	0.46	0.57	0.55
high	0.88	0.69	0.91	0.95	0.87	0.95	0.82	1.03	0.73	0.74	0.95	0.84	0.98
10-1	1.93	1.83	2.07	2.12	2.03	2.02	1.73	1.88	1.77	1.87	2.03	2.07	1.92
t(10-1)	(13.50)	(11.06)	(11.94)	(13.16)	(12.65)	(12.80)	(10.60)	(12.09)	(12.47)	(11.20)	(12.44)	(11.75)	(12.04)

Panel B: Annual Recency Adjustment RA_A

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	-0.78	-0.75	-0.81	-0.71	-0.87	-0.49	-0.62	-0.61	-0.74	-0.75	-0.78	-0.78	-0.58
2	-0.39	-0.35	-0.34	-0.39	-0.38	-0.09	-0.35	-0.29	-0.38	-0.33	-0.37	-0.43	-0.27
3	-0.18	-0.15	-0.16	-0.21	-0.13	-0.06	-0.21	-0.19	-0.15	-0.16	-0.19	-0.13	-0.18
4	-0.06	-0.01	-0.01	-0.03	-0.01	0.12	-0.07	-0.06	0.01	-0.03	-0.06	-0.02	0.05
5	0.08	0.19	0.15	0.11	0.06	0.16	0.08	0.06	0.11	0.16	0.08	0.13	0.06
6	0.25	0.21	0.16	0.22	0.25	0.22	0.19	0.07	0.24	0.21	0.19	0.24	0.20
7	0.30	0.35	0.31	0.31	0.33	0.30	0.30	0.36	0.34	0.30	0.38	0.38	0.30
8	0.47	0.44	0.45	0.39	0.47	0.27	0.45	0.39	0.47	0.45	0.43	0.51	0.37
9	0.60	0.57	0.63	0.67	0.65	0.42	0.66	0.59	0.59	0.61	0.58	0.55	0.56
high	1.01	0.74	0.92	0.90	0.90	0.42	0.85	0.94	0.76	0.79	1.01	0.83	0.78
10-1	1.79	1.48	1.73	1.61	1.77	0.91	1.47	1.54	1.50	1.54	1.79	1.61	1.36
t(10-1)	(10.25)	(8.58)	(9.18)	(8.21)	(9.33)	(5.67)	(9.31)	(9.45)	(10.55)	(8.58)	(9.74)	(8.53)	(8.02)

Table 17. Double Sorts based on Recency Adjustment – Equally-Weighted Raw Returns
This table reports monthly subsequent raw returns from double portfolio sorts. First, within each month, each stock is allocated to a decile portfolio based on one of the control variables BETA, ln(MV), BM, MOM, ltREV, REV, IVOL, MAX, MIN, ILLIQ, RR, TK, or ST as introduced in Table 1. Second, within each decile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A and RA_A in Panel B. RA_M is the recency adjustment for the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. For each of the resulting 100 portfolios, the equally-weighted return is calculated. These 100 portfolio returns are then aggregated across the first sorting criterion, that is, the reported RA-decile returns are computed as the average return among the ten corresponding portfolios sorted by one of the control variables. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns are stated in %.

Panel A: Monthly Recency Adjustment RA_M

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	0.21	0.07	0.09	0.10	0.05	0.19	0.30	0.38	0.18	0.08	0.18	0.01	0.28
2	0.98	0.83	0.83	0.87	0.89	0.87	0.76	0.80	0.82	0.78	0.91	0.89	0.83
3	1.17	1.10	1.13	1.07	1.14	1.07	1.01	0.98	1.08	1.14	1.08	1.14	1.08
4	1.17	1.27	1.24	1.21	1.23	1.18	1.21	1.19	1.26	1.27	1.26	1.28	1.22
5	1.33	1.38	1.35	1.33	1.34	1.36	1.28	1.30	1.32	1.39	1.29	1.37	1.26
6	1.33	1.51	1.35	1.40	1.44	1.33	1.45	1.36	1.47	1.47	1.39	1.38	1.37
7	1.44	1.55	1.54	1.45	1.56	1.42	1.57	1.50	1.55	1.60	1.47	1.51	1.47
8	1.52	1.68	1.63	1.59	1.59	1.64	1.73	1.63	1.70	1.62	1.61	1.59	1.59
9	1.79	1.79	1.83	1.81	1.79	1.80	1.82	1.75	1.83	1.82	1.72	1.82	1.79
high	2.17	1.96	2.16	2.31	2.14	2.27	2.05	2.24	1.93	1.97	2.26	2.14	2.24
10-1	1.97	1.88	2.06	2.21	2.09	2.08	1.75	1.86	1.76	1.89	2.07	2.13	1.96
t(10-1)	(14.30)	(12.61)	(13.99)	(14.31)	(13.74)	(13.74)	(11.31)	(12.82)	(13.65)	(12.74)	(14.19)	(13.36)	(12.95)

Panel B: Annual Recency Adjustment RA_A

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	0.53	0.53	0.48	0.64	0.46	0.78	0.62	0.61	0.55	0.50	0.54	0.54	0.68
2	0.86	0.86	0.88	0.85	0.83	1.08	0.86	0.92	0.81	0.89	0.87	0.80	0.93
3	1.01	1.05	1.02	1.00	1.06	1.14	0.97	1.00	1.05	1.02	1.01	1.05	1.03
4	1.10	1.18	1.17	1.11	1.17	1.25	1.11	1.11	1.19	1.14	1.07	1.18	1.19
5	1.25	1.35	1.32	1.24	1.23	1.30	1.25	1.22	1.26	1.37	1.22	1.26	1.21
6	1.39	1.40	1.32	1.36	1.40	1.35	1.36	1.24	1.43	1.37	1.31	1.37	1.31
7	1.43	1.51	1.48	1.44	1.50	1.44	1.47	1.52	1.48	1.47	1.51	1.49	1.46
8	1.60	1.60	1.59	1.53	1.61	1.45	1.58	1.52	1.61	1.60	1.59	1.66	1.53
9	1.73	1.80	1.82	1.82	1.80	1.65	1.87	1.80	1.77	1.80	1.77	1.73	1.75
high	2.27	1.91	2.11	2.14	2.09	1.71	2.08	2.21	1.99	1.97	2.25	2.08	2.07
10-1	1.74	1.38	1.63	1.49	1.63	0.92	1.46	1.61	1.44	1.47	1.71	1.54	1.40
t(10-1)	(9.55)	(8.89)	(10.46)	(7.33)	(10.11)	(5.06)	(9.90)	(9.03)	(10.43)	(9.48)	(10.32)	(9.27)	(8.13)

Table 18. Double Sorts based on Recency Adjustment – Value-Weighted Raw Returns
This table reports monthly subsequent raw returns from double portfolio sorts. First, within each month, each stock is allocated to a decile portfolio based on one of the control variables BETA, ln(MV), BM, MOM, ltREV, REV, IVOL, MAX, MIN, ILLIQ, RR, TK, or ST as introduced in Table 1. Second, within each decile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A and RA_A in Panel B. RA_M is the recency adjustment for the previous month and is calculated as the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. For each of the resulting 100 portfolios, the value-weighted return is calculated. These 100 portfolio returns are then aggregated across the first sorting criterion, that is, the reported RA-decile returns are computed as the average return among the ten corresponding portfolios sorted by one of the control variables. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns are stated in %.

Panel A: Monthly Recency Adjustment RA_M

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	0.33	0.02	0.29	0.12	0.28	0.43	0.25	0.38	0.26	0.05	0.28	0.21	0.38
2	0.85	0.81	0.72	0.70	0.85	0.71	0.62	0.67	0.70	0.73	0.66	0.71	0.64
3	0.94	1.08	1.00	0.83	0.95	0.94	0.80	0.78	0.91	1.05	0.89	0.97	0.93
4	0.96	1.25	1.14	0.92	1.12	0.99	1.01	1.02	1.10	1.19	1.01	1.09	1.06
5	1.11	1.35	1.20	1.15	1.19	1.15	1.10	1.07	1.17	1.30	1.03	1.22	1.01
6	1.12	1.47	1.16	1.10	1.23	1.21	1.16	1.06	1.17	1.40	1.12	1.19	1.17
7	1.13	1.49	1.33	1.17	1.26	1.16	1.27	1.16	1.24	1.51	1.12	1.29	1.18
8	1.21	1.65	1.41	1.25	1.35	1.41	1.37	1.32	1.31	1.60	1.29	1.32	1.24
9	1.42	1.74	1.60	1.38	1.43	1.45	1.41	1.35	1.44	1.73	1.34	1.43	1.44
high	1.71	1.87	1.75	1.65	1.79	1.71	1.68	1.74	1.60	1.91	1.59	1.74	1.65
10-1	1.37	1.85	1.45	1.53	1.51	1.28	1.43	1.36	1.34	1.86	1.31	1.53	1.27
t(10-1)	(10.62)	(12.07)	(11.11)	(10.43)	(9.95)	(8.84)	(8.46)	(9.50)	(9.79)	(11.74)	(10.05)	(9.03)	(9.03)

Panel B: Annual Recency Adjustment RA_A

	BETA	ln(MV)	BM	MOM	ltREV	REV	IVOL	MAX	MIN	ILLIQ	RR	TK	ST
low	0.63	0.52	0.60	0.59	0.55	0.76	0.54	0.51	0.49	0.55	0.61	0.57	0.60
2	0.67	0.86	0.84	0.64	0.82	0.89	0.81	0.78	0.70	0.87	0.69	0.79	0.77
3	0.85	1.04	0.89	0.78	0.94	0.91	0.86	0.85	0.88	1.01	0.84	0.96	0.85
4	0.94	1.17	1.00	0.91	1.03	1.03	0.87	0.94	0.96	1.09	0.92	1.00	0.95
5	1.09	1.33	1.18	1.04	1.03	1.09	1.06	1.03	1.02	1.32	0.95	1.08	1.04
6	1.23	1.38	1.28	1.17	1.19	1.12	1.10	1.08	1.18	1.34	1.17	1.25	1.10
7	1.25	1.48	1.33	1.23	1.30	1.23	1.21	1.25	1.25	1.47	1.28	1.28	1.36
8	1.41	1.56	1.46	1.35	1.39	1.31	1.28	1.24	1.35	1.59	1.33	1.42	1.31
9	1.50	1.74	1.69	1.55	1.58	1.41	1.48	1.44	1.45	1.77	1.50	1.49	1.47
high	1.91	1.80	1.86	1.68	1.83	1.64	1.68	1.75	1.74	1.86	1.78	1.78	1.71
10-1	1.28	1.27	1.26	1.09	1.27	0.88	1.14	1.24	1.25	1.31	1.17	1.21	1.12
t(10-1)	(8.44)	(8.35)	(8.00)	(5.47)	(7.35)	(4.58)	(7.10)	(7.23)	(7.83)	(8.68)	(7.21)	(7.52)	(6.22)

Table 19. Conditional Double Sorts – Equally-Weighted FFC-Adjusted Returns
This table reports monthly equally-weighted FFC-adjusted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a quartile portfolio based on ILLIQ, IVOL, or MAX(|ret|). ILLIQ is the Amihud (2002) illiquidity measure based on daily returns of the previous year. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX(|ret|) is the maximum absolute daily return of the previous month. Second, within each quartile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A or based on RA_A in Panel B. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The FFC-adjusted returns are stated in %.

Panel A: Portfolios Sorted by RA_M

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	-0.40	-0.75	-1.25	-2.20	-0.11	-0.46	-0.86	-2.35	-0.03	-0.46	-0.89	-2.27
2	-0.20	-0.20	-0.28	-0.67	0.08	-0.14	-0.23	-1.33	0.14	-0.02	-0.50	-1.36
3	-0.01	-0.09	0.09	-0.05	0.13	0.09	-0.04	-0.68	0.25	0.12	-0.02	-0.64
4	0.04	0.03	0.15	0.12	0.21	0.12	0.06	-0.44	0.30	0.09	-0.09	-0.48
5	0.14	0.20	0.33	0.31	0.27	0.25	0.25	-0.15	0.26	0.34	0.13	-0.23
6	0.11	0.20	0.32	0.43	0.14	0.26	0.40	0.10	0.31	0.28	0.29	0.22
7	0.14	0.27	0.29	0.60	0.23	0.36	0.44	0.54	0.23	0.38	0.33	0.35
8	0.14	0.39	0.54	0.81	0.30	0.43	0.63	0.66	0.31	0.48	0.60	0.42
9	0.20	0.36	0.41	1.32	0.30	0.53	0.59	1.05	0.40	0.50	0.57	0.86
high	0.32	0.38	0.76	1.75	0.35	0.72	0.96	1.35	0.51	0.83	1.07	1.39
10-1	0.73	1.13	2.01	3.95	0.46	1.19	1.82	3.69	0.53	1.29	1.96	3.66
t(10-1)	(4.79)	(5.28)	(10.08)	(12.87)	(3.54)	(7.54)	(10.32)	(11.68)	(4.59)	(9.85)	(10.17)	(11.68)

Panel B: Portfolios Sorted by RA_A

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	-0.35	-0.46	-0.60	-1.60	-0.21	-0.30	-0.45	-1.80	-0.10	-0.22	-0.49	-1.79
2	-0.29	-0.33	-0.35	-0.60	-0.08	-0.18	-0.14	-0.98	-0.01	-0.22	-0.30	-0.98
3	-0.16	-0.14	-0.00	-0.36	-0.04	-0.11	-0.07	-0.79	0.17	-0.05	-0.16	-0.60
4	-0.11	-0.07	0.01	-0.00	0.13	0.06	0.15	-0.34	0.07	0.17	-0.01	-0.61
5	0.10	0.04	0.32	0.33	0.17	0.14	0.24	-0.15	0.28	0.21	-0.01	-0.13
6	0.10	0.14	0.16	0.37	0.27	0.21	0.27	0.03	0.18	0.20	0.19	-0.08
7	0.18	0.26	0.36	0.56	0.27	0.28	0.43	0.27	0.33	0.38	0.43	0.15
8	0.20	0.36	0.43	0.85	0.32	0.56	0.50	0.40	0.50	0.66	0.51	0.23
9	0.33	0.42	0.50	1.27	0.46	0.66	0.49	0.83	0.52	0.62	0.53	0.83
high	0.49	0.55	0.53	1.64	0.61	0.81	0.78	1.36	0.70	0.82	0.82	1.30
10-1	0.84	1.02	1.13	3.24	0.82	1.12	1.24	3.16	0.80	1.04	1.31	3.10
t(10-1)	(4.44)	(4.97)	(5.11)	(11.52)	(5.15)	(7.33)	(6.42)	(9.76)	(5.52)	(7.30)	(6.68)	(9.53)

Table 20. Conditional Double Sorts – Equally-Weighted Raw Returns
This table reports monthly equally-weighted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a quartile portfolio based on ILLIQ, IVOL, or MAX(|ret|). ILLIQ is the Amihud (2002) illiquidity measure based on daily returns of the previous year. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX(|ret|) is the maximum absolute daily return of the previous month. Second, within each quartile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A or based on RA_A in Panel B. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The returns are stated in %.

Panel A: Portfolios Sorted by RA_M

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	0.57	0.35	0.02	-0.71	0.90	0.70	0.38	-0.89	0.95	0.69	0.39	-0.78
2	0.79	0.88	0.92	0.72	1.01	0.98	0.95	0.04	1.02	1.06	0.76	0.01
3	0.93	0.98	1.35	1.35	1.04	1.23	1.16	0.68	1.15	1.26	1.22	0.78
4	0.97	1.14	1.33	1.54	1.13	1.21	1.31	1.06	1.15	1.23	1.20	1.00
5	1.11	1.26	1.51	1.69	1.20	1.37	1.45	1.31	1.22	1.47	1.39	1.24
6	1.08	1.28	1.47	1.90	1.06	1.38	1.62	1.50	1.19	1.39	1.59	1.56
7	1.12	1.37	1.55	2.08	1.16	1.48	1.71	1.99	1.11	1.53	1.58	1.74
8	1.10	1.50	1.78	2.25	1.22	1.59	1.93	2.04	1.22	1.57	1.93	1.84
9	1.18	1.52	1.71	2.77	1.29	1.66	2.00	2.37	1.32	1.65	2.00	2.25
high	1.38	1.60	1.94	3.27	1.42	1.90	2.20	2.79	1.56	1.96	2.33	2.79
10-1	0.81	1.25	1.92	3.98	0.52	1.20	1.82	3.68	0.61	1.28	1.94	3.57
t(10-1)	(6.19)	(5.89)	(11.38)	(13.76)	(4.34)	(7.67)	(10.49)	(13.00)	(4.63)	(9.81)	(10.17)	(13.30)

Panel B: Portfolios Sorted by RA_A

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	0.68	0.70	0.72	-0.15	0.77	0.87	0.98	-0.40	0.84	1.02	0.87	-0.38
2	0.70	0.83	1.00	0.86	0.90	0.98	1.11	0.46	0.93	0.89	1.01	0.51
3	0.84	0.96	1.18	1.06	0.91	1.06	1.16	0.61	1.05	1.04	1.13	0.81
4	0.86	1.01	1.28	1.44	1.04	1.18	1.38	1.11	1.01	1.29	1.23	0.85
5	1.01	1.14	1.47	1.83	1.08	1.23	1.45	1.25	1.15	1.30	1.28	1.27
6	1.03	1.27	1.39	1.79	1.17	1.32	1.54	1.45	1.09	1.30	1.44	1.37
7	1.14	1.30	1.56	1.94	1.17	1.40	1.65	1.64	1.21	1.51	1.67	1.53
8	1.14	1.46	1.63	2.24	1.27	1.63	1.72	1.76	1.39	1.72	1.77	1.60
9	1.34	1.53	1.65	2.63	1.43	1.79	1.71	2.20	1.47	1.73	1.80	2.14
high	1.49	1.69	1.71	3.25	1.70	2.01	2.04	2.88	1.75	1.98	2.19	2.79
10-1	0.81	0.99	0.99	3.40	0.92	1.14	1.06	3.28	0.90	0.95	1.32	3.17
t(10-1)	(4.72)	(5.34)	(5.20)	(10.25)	(5.78)	(7.82)	(6.40)	(8.54)	(6.45)	(7.19)	(6.64)	(9.11)

Table 21. Conditional Double Sorts – Value-Weighted Raw Returns
This table reports monthly value-weighted subsequent returns from double portfolio sorts. First, within each month, each stock is allocated to a quartile portfolio based on ILLIQ, IVOL, or MAX(|ret|). ILLIQ is the Amihud (2002) illiquidity measure based on daily returns of the previous year. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX(|ret|) is the maximum absolute daily return of the previous month. Second, within each quartile portfolio, each stock is allocated to a decile portfolio based on RA_M in Panel A or based on RA_A in Panel B. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The returns are stated in %.

Panel A: Portfolios Sorted by RA_M

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	0.52	0.33	0.17	-0.94	0.70	0.48	0.25	-0.46	0.72	0.51	0.42	-0.35
2	0.72	0.86	0.82	0.49	0.86	0.67	0.80	0.07	0.79	0.82	0.65	0.19
3	0.90	0.90	1.21	0.99	0.84	0.99	0.96	0.29	0.90	1.02	1.06	0.43
4	0.94	1.04	1.23	1.41	0.97	0.99	1.12	0.67	1.03	0.95	1.09	0.95
5	0.94	1.20	1.45	1.51	1.07	1.11	1.17	1.15	1.07	1.24	1.03	1.02
6	1.01	1.18	1.45	1.68	0.93	1.08	1.40	1.14	1.03	1.15	1.19	1.19
7	1.01	1.30	1.50	1.86	1.06	1.21	1.21	1.31	0.93	1.12	1.21	0.98
8	0.99	1.51	1.80	1.94	1.10	1.29	1.47	1.52	1.08	1.31	1.65	1.29
9	1.09	1.46	1.67	2.43	1.09	1.18	1.54	1.60	1.14	1.11	1.58	1.55
high	1.29	1.74	2.03	2.53	1.27	1.53	1.98	1.68	1.28	1.56	1.91	1.66
10-1	0.77	1.40	1.86	3.47	0.57	1.06	1.73	2.14	0.56	1.06	1.48	2.01
t(10-1)	(5.43)	(5.74)	(10.15)	(11.65)	(4.09)	(5.63)	(8.35)	(6.89)	(4.28)	(6.50)	(6.03)	(6.85)

Panel B: Portfolios Sorted by RA_A

	ILLIQ				IVOL				MAX(|ret|)			
	low	2	3	high	low	2	3	high	low	2	3	high
low	0.59	0.67	0.93	-0.09	0.59	0.48	0.81	-0.11	0.66	0.57	0.79	0.05
2	0.70	0.71	0.91	0.81	0.70	0.80	0.95	0.59	0.66	0.71	0.74	0.65
3	0.81	0.97	1.11	1.07	0.82	0.93	1.02	0.69	0.86	0.97	0.99	0.93
4	0.73	1.04	1.30	1.34	0.85	1.00	0.96	0.76	0.81	1.04	0.95	0.70
5	0.98	1.08	1.37	1.67	0.95	0.83	1.14	0.91	0.83	0.98	1.02	1.03
6	1.01	1.32	1.34	1.63	1.14	1.02	1.17	1.12	1.04	1.18	1.01	1.04
7	1.12	1.31	1.55	1.74	1.04	1.17	1.23	1.10	1.04	1.16	1.41	0.96
8	1.13	1.41	1.64	1.90	1.15	1.39	1.48	0.94	1.32	1.33	1.50	0.97
9	1.24	1.55	1.73	2.22	1.22	1.40	1.41	1.41	1.30	1.47	1.64	1.18
high	1.47	1.82	1.68	2.40	1.60	1.74	1.59	1.55	1.71	1.72	1.84	1.49
10-1	0.88	1.15	0.75	2.49	1.01	1.26	0.78	1.66	1.05	1.14	1.05	1.44
t(10-1)	(4.89)	(6.24)	(3.77)	(8.19)	(6.26)	(6.07)	(3.93)	(4.02)	(6.25)	(5.99)	(4.95)	(4.01)

Table 22. Recency Adjustment in Fama-MacBeth-Regressions – Interaction Terms
This table reports Fama-MacBeth-regression estimates based on monthly data. The dependent variable is the stock return of the subsequent month. ILLIQ is the Amihud (2002) illiquidity measure based on daily returns of the previous year. IVOL is the idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MAX(|ret|) is the maximum absolute daily return of the previous month. RA_M is the recency adjustment for the previous month, that is the covariance between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. The sample period is January 1931 to December 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: RA_M and its Interaction Effects

	(1)	(2)	(3)
intercept	1.3649	1.3329	1.3296
	(8.61)	(8.71)	(8.72)
RA_M	0.1533	0.1300	0.1522
	(17.19)	(8.86)	(10.70)
ILLIQ	0.0378	0.0316	0.0314
	(3.30)	(3.29)	(3.25)
IVOL	-0.0204	0.1225	0.0811
	(-0.04)	(0.24)	(0.17)
MAX(|ret|)	-0.0455	-0.0499	-0.0484
	(-3.44)	(-3.75)	(-3.63)
RA_MxILLIQ	0.0051		
	(3.06)		
RA_MxIVol		0.1096	
		(4.25)	
RA_MxMAX(|ret|)			0.0031
			(2.85)

Panel B: RA_A and its Interaction Effects

	(1)	(2)	(3)
intercept	1.3074	1.2333	1.2682
	(7.88)	(7.71)	(8.07)
RA_A	0.0317	0.0173	0.0219
	(8.48)	(2.83)	(3.60)
ILLIQ	0.0363	0.0299	0.0296
	(3.67)	(3.40)	(3.39)
IVOL	-0.5058	-0.1881	-0.4505
	(-1.11)	(-0.36)	(-0.98)
MAX(|ret|)	-0.0224	-0.0240	-0.0151
	(-1.74)	(-1.83)	(-1.11)
RA_AxILLIQ	0.0017		
	(3.81)		
RA_AxIVol		0.0455	
		(3.31)	
RA_AxMAX(|ret|)			0.0018
			(2.89)

Table 23. Portfolio Sorts Based on Recency Adjustment – Different Formation Periods
This table reports monthly decile portfolio sorts based on recency adjustment RA. RA is the recency adjustment based on the previous 6, 12, 36, or 60 months, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. Subsequent Fama-French-Carhart-adjusted returns are provided for both equally- and value-weighted portfolios. The sample period is January 1931 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Fama-French-Carhart-adjusted returns are stated in %.

	RA_{6M}		RA_{12M}		RA_{36M}		RA_{60M}	
	ew	vw	ew	vw	ew	vw	ew	vw
low	-0.94	-0.57	-0.87	-0.63	-0.42	-0.43	-0.25	-0.31
2	-0.29	-0.27	-0.37	-0.34	-0.18	-0.33	-0.09	-0.23
3	0.00	-0.08	-0.18	-0.27	-0.08	-0.16	-0.08	-0.13
4	0.11	0.03	0.04	-0.07	-0.05	-0.07	0.03	-0.07
5	0.15	-0.02	0.09	-0.07	0.10	-0.04	0.17	0.01
6	0.24	0.01	0.19	0.15	0.20	0.10	0.21	0.07
7	0.31	0.15	0.31	0.23	0.22	0.18	0.18	0.11
8	0.33	0.07	0.45	0.32	0.31	0.16	0.33	0.18
9	0.55	0.25	0.59	0.42	0.50	0.36	0.35	0.27
high	0.79	0.13	1.01	0.56	0.65	0.40	0.41	0.25
10-1	1.73	0.70	1.88	1.19	1.07	0.83	0.66	0.56
t(10-1)	(8.25)	(2.80)	(8.84)	(6.00)	(6.55)	(4.53)	(4.37)	(3.17)

Table 24. Recency Adjustment in Fama-MacBeth-Regressions – Different Formation Periods
This table reports Fama-MacBeth-regression estimates based on monthly data. The dependent variable is the stock return of the subsequent month. RA is the recency adjustment based on the previous 6, 12, 36, or 60 months, that is the covariance between monthly returns and the corresponding number of months until portfolio formation. All RA-estimates are standardized to have the same standard deviation as RA_{12M}. The other explanatory variables are described in Table 1. The sample period is January 1931 to December 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	RA_{6M}	RA_{12M}	RA_{36M}	RA_{60M}
intercept	3.1256	3.0098	3.0254	3.0877
	(5.27)	(4.90)	(5.00)	(5.12)
RA	0.0084	0.0120	0.0111	0.0066
	(2.13)	(3.96)	(3.19)	(2.27)
BETA	0.0111	0.0235	0.0246	0.0313
	(0.10)	(0.21)	(0.24)	(0.30)
ln(MV)	-0.1354	-0.1315	-0.1316	-0.1327
	(-4.77)	(-4.49)	(-4.60)	(-4.64)
BM	0.0822	0.0798	0.0810	0.0748
	(3.12)	(3.04)	(3.15)	(2.85)
MOM	0.0049	0.0048	0.0072	0.0065
	(2.51)	(2.34)	(3.29)	(3.84)
ltREV	-0.0004	-0.0004	-0.0006	-0.0006
	(-1.19)	(-1.04)	(-1.83)	(-1.66)
REV	-0.0625	-0.0621	-0.0641	-0.0653
	(-13.39)	(-14.68)	(-15.13)	(-15.17)
IVOL	-0.0531	-0.1471	-0.1611	-0.1185
	(-0.15)	(-0.41)	(-0.47)	(-0.34)
MAX	0.0080	0.0090	0.0088	0.0073
	(0.64)	(0.72)	(0.71)	(0.59)
MIN	0.0775	0.0737	0.0755	0.0760
	(5.94)	(5.60)	(5.75)	(5.87)
ILLIQ	0.0195	0.0200	0.0199	0.0201
	(3.05)	(3.10)	(3.08)	(3.14)
RR	0.7483	0.7831	0.7589	0.7519
	(7.44)	(8.53)	(8.06)	(7.57)
TK	-3.5221	-3.6089	-4.1008	-4.0111
	(-2.27)	(-2.29)	(-2.57)	(-2.53)
ST	-0.0634	-0.0646	-0.0643	-0.0655
	(-4.11)	(-4.17)	(-4.16)	(-4.23)

Table 25. Portfolio Sorts Based on Correlation-Based Recency Adjustment
This table reports monthly decile portfolio sorts based on monthly recency adjustment, RA_M, in Panel A and annual recency adjustment, RA_A, in Panel B. RA_M is based on the previous month and is calculated as the (rank) correlation between daily returns and the corresponding number of trading days until the end of month. RA_A is the recency adjustment for the previous year, that is the (rank) correlation between monthly returns and the corresponding number of months until portfolio formation. Subsequent portfolio returns are provided on an equally- or value-weighted raw or FFC-adjusted basis. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Returns and alphas are stated in %.

Panel A: Monthly Recency Adjustment

	RA_M Based on Correlation				RA_M Based on Rank Correlation			
	equally-weighted		value-weighted		equally-weighted		value-weighted	
	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}
low	0.32	-0.87	0.51	-0.51	0.43	-0.71	0.56	-0.41
2	0.74	-0.41	0.73	-0.25	0.75	-0.44	0.69	-0.30
3	0.97	-0.20	0.91	-0.08	0.99	-0.24	0.86	-0.13
4	1.19	-0.07	0.97	-0.04	1.20	0.01	1.04	0.04
5	1.35	0.17	1.07	0.12	1.28	0.09	1.00	0.03
6	1.48	0.26	1.05	0.10	1.41	0.20	1.04	0.07
7	1.63	0.43	1.02	0.06	1.59	0.38	1.11	0.15
8	1.67	0.47	1.09	0.10	1.79	0.55	1.07	0.09
9	1.86	0.66	1.13	0.18	1.74	0.59	1.17	0.24
high	1.93	0.80	1.34	0.41	1.96	0.83	1.30	0.38
10-1	1.61	1.67	0.83	0.91	1.54	1.55	0.74	0.78
t(10-1)	(11.40)	(10.48)	(6.81)	(6.14)	(11.76)	(10.99)	(6.11)	(6.04)

Panel B: Annual Recency Adjustment

	RA_A Based on Correlation				RA_A Based on Rank Correlation			
	equally-weighted		value-weighted		equally-weighted		value-weighted	
	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}	R	α_{FFC}
low	0.59	-0.59	0.48	-0.51	0.75	-0.46	0.48	-0.49
2	0.80	-0.43	0.79	-0.22	0.90	-0.34	0.83	-0.17
3	0.92	-0.27	0.81	-0.20	0.93	-0.28	0.83	-0.20
4	1.11	-0.12	0.78	-0.22	1.14	-0.07	0.87	-0.11
5	1.28	0.07	0.98	-0.01	1.27	0.03	1.02	-0.01
6	1.36	0.15	1.18	0.28	1.31	0.10	1.05	0.05
7	1.47	0.27	1.02	0.03	1.41	0.23	1.09	0.11
8	1.62	0.45	1.09	0.13	1.61	0.44	1.12	0.16
9	1.82	0.69	1.32	0.36	1.74	0.59	1.16	0.25
high	2.16	1.05	1.52	0.60	2.07	1.01	1.45	0.57
10-1	1.57	1.64	1.03	1.11	1.32	1.47	0.97	1.06
t(10-1)	(10.33)	(10.05)	(7.14)	(8.41)	(10.34)	(10.05)	(6.81)	(7.99)