Decomposing Momentum: Eliminating its Crash Component

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Abstract: We propose a purely cross-sectional momentum strategy that avoids crash risk and does not depend on the state of the market. To do so, we simply split up the standard momentum return over months $t-12$ to $t-2$ at the highest stock price within this formation period. Both resulting momentum return components predict subsequent returns on a stand-alone basis. However, the long-short returns associated with the first component completely avoid negative skewness since momentum crashes are entirely driven by the second component.

Keywords: Momentum, Momentum Crashes, 52-Week High, Cross-Section of Stock Returns, Return Predictability

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1. Introduction

The winner stocks of the previous year tend to subsequently outperform the loser stocks of the previous year (Jegadeesh and Titman, 1993). This momentum effect is one of the most pervasive anomalies in the cross-section of stock returns. A long-short portfolio that is long in the highest decile of momentum stocks and short in the lowest decile yields an average monthly return of 1.21% per month over a time period from 1927 to 2018. At the same time, research has shown that momentum strategies exhibit rare but severe crashes (Daniel and Moskowitz, 2016). Indeed, momentum is highly left-skewed and fat-tailed. The strategy's worst monthly return is -77.56%. Momentum tends to crash when the market rebounds after a severe market downturn. In these situations, the market risk exposure of the long-short momentum strategy is strongly negative, implying low returns in form of crashes when the market rises. Examples of such periods are the Great Depression in the 1930s and the financial crisis in 2009.

In this paper, we show that a simple decomposition of momentum allows to avoid these crashes. More specifically, we empirically decompose momentum (MOM) into the two components price-to-high (PTH) and high-to-price (HTP) and show that only PTH causes the well-known momentum crashes. Upon removing PTH from MOM, the remaining momentum component HTP induces significantly positive long-short returns without negative skewness, i.e., a crash-free alternative to the standard momentum strategy. Our decomposition approach simply relies on the highest stock price P_{high} during the conventional momentum formation period over months $t-12$ to $t-2$. Utilizing P_{high}, HTP

can be expressed as the difference between log momentum return (MOM) and PTH:

$$HTP = ln\left(\frac{P_{high}}{P_0}\right) = ln\left(\frac{P_1}{P_0}\right) - ln\left(\frac{P_1}{P_{high}}\right) = MOM - PTH \tag{1}$$

where P_0 and P_1 denote the stock price at the beginning ($t-12$) and the end ($t-2$) of the momentum formation period, respectively. Previous research has extensively documented the positive cross-sectional relationship between MOM and subsequent returns. Moreover, PTH – conceptually similar to the 52-week high measure of George and Hwang (2004) – has been shown to predict subsequent returns and to partly explain momentum profits. However, to the best of our knowledge, the remaining component HTP has not yet been investigated – although a corresponding long-short strategy yields highly significant return premiums while allowing to circumvent momentum crashes at the same time.

More specifically, our analyses show that the momentum component PTH generates a value-weighted decile return spread of 0.52% per month and a Sharpe ratio of 0.21. The corresponding long-short returns are severely left-skewed and responsible for the well-documented momentum crashes (Daniel and Moskowitz, 2016). We find that the PTH-strategy suffers from even worse crashes than traditional momentum. Both MOM- and PTH-strategy strongly depend on market conditions as they yield positive return spreads only in up market states (Cooper et al., 2004) and in times of low cross-sectional return dispersion (Stivers and Sun, 2010). Following market downturns, the PTH-strategy's short leg – by construction – contains the most severe recent loser stocks. When the market rebounds from these bear markets, the loser stocks sharply increase in value, leading to a negative market risk exposure and crashes of the PTH-strategy.

Upon removing this crash-prone *PTH*-component from momentum, the remaining component *HTP* yields a monthly return premium of 1.18% and a Sharpe ratio of 0.71 – thereby outperforming the traditional momentum strategy (Sharpe ratio of 0.54). Moreover, the long-short returns associated with *HTP* are slightly positively skewed and show no signs of crashes when the market rebounds after a severe downturn. This results in substantially higher buy-and-hold returns for the *HTP*-strategy compared to *MOM*- and *PTH*-strategy. Moreover, *HTP* induces significantly positive return spreads in both up and down market states (Cooper et al., 2004) as well as in both times of high and low cross-sectional return dispersion (Stivers and Sun, 2010). As the *HTP*-strategy's short leg largely avoids recent loser stocks, it neither shows a negative market risk exposure nor crashes when these loser stocks recover after severe market drawdowns.

Beyond separately investigating *PTH*- and *HTP*-strategy, we also examine how these two components jointly contribute to the momentum effect. First, both components add to the overall profitability of momentum. Second, the *PTH*-strategy (*HTP*-strategy) is closely related to the momentum short leg (long leg). Third, after market downturns, momentum is largely determined by its *PTH*-component such that it crashes similarly as the *PTH*-strategy and cannot profit from the crash-resilient nature of *HTP*.

Our contribution to the literature is mainly threefold. First, our analyses add to previous research on the 52-week high as *PTH* roughly reflects a stock's proximity to this maximum price. In line with our findings on *PTH*, George and Hwang (2004) show that stocks close to their 52-week high subsequently outperform stocks far from their 52-week high and argue that this effect contributes to momentum profits. Building on the seminal findings of George and Hwang (2004), the implications of a stock's distance from its 52-week high have been examined extensively in recent years (see for example, Huddart et al., 2009; Driessen

et al., 2012; Bhootra and Hur, 2013; Lee and Piqueira, 2017; George et al., 2017, 2018; Zhu, 2020). While these papers focus on a stock's return after the 52-week high, we examine its return prior to the 52-week high. This complementing momentum component HTP has not received any explicit research attention yet. For example, the regression analyses in George and Hwang (2004) and Byun et al. (2020) indicate that MOM indeed remains a significant return predictor after controlling for PTH. But so far, research has neither acknowledged that this remaining effect is by construction due to HTP nor examined its strong return predictability – although HTP-based long-short portfolios even generate higher returns and Sharpe ratios compared to the previously examined PTH-based strategies.

Second, we contribute to the extensive debate on momentum crashes and its sources (Chabot et al., 2014; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Daniel et al., 2019). We show that the crashes can be completely attributed to the momentum component PTH. Upon removing PTH, a purely cross-sectional momentum strategy based on HTP completely avoids negative return skewness. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) reduce momentum crash risk by the use of dynamic strategies. They show that the volatility of momentum strategy returns predicts momentum crashes. Consequently, their dynamic strategies allow to avoid severe momentum crashes by systematically reducing the investment exposure during high-volatility periods. We show that a simple static cross-sectional strategy based on HTP can also avoid these crashes, but without any time-series adjustments of investment exposure, i.e., we propose a new simple method to reduce the risk of momentum investing. Notably, the average returns and Sharpe ratios of the new HTP-based momentum strategy provide an additional challenge to existing theories that aim at explaining the overall momentum phenomenon. For example, our findings imply that momentum profits are not merely a compensation for

momentum crashes as we can hedge out these crashes without sacrificing cross-sectional return predictability.

Third, we add to the large literature strand examining further time-series properties of momentum. Grundy and Martin (2001) show that the market risk exposure of momentum strategies is negative following market downturns (also see Wang and Wu, 2011; Kelly et al., 2021; and Theissen and Yilanci, 2021 on momentum's time-varying risk exposure). This property is due to PTH but not HTP. In addition, Cooper et al. (2004) and Stivers and Sun (2010) document that momentum profits are strong in market up states and in times of low cross-sectional return dispersion but vanish otherwise. Again, these time-series properties are entirely due to the PTH component of momentum and absent for HTP. Put differently, up market states and low cross-sectional return dispersion are no necessary conditions for momentum profits to arise – the momentum component HTP generates significantly positive returns irrespective of these market states.

The remainder of this paper is structured as follows. Section 2 introduces the data set and the main variables. Section 3 provides evidence on the return predictability associated with MOM, HTP, and PTH with a particular focus on their crash properties and market state dependence. The underlying drivers of the long-short strategies' different crash risk are examined in Section 4. Finally, we discuss how HTP and PTH contribute to the overall momentum effect in Section 5 and conclude in Section 6.

2. Data and Variables

Our stock market analyses are mainly based on return data obtained from the Center for Research in Security Prices (CRSP). Risk-free rate and Fama and French (1993) three factor

data is obtained from Kenneth R. French's homepage.[1] Accounting data is retrieved from COMPUSTAT. In line with Fama and French (1993), we use annual balance sheet data at the earliest at the end of June of the following year.[2]

The key stock-level variables momentum return (MOM), high-to-price (HTP), and price-to-high (PTH) are calculated based on CRSP data. MOM is defined as the log return over the previous year skipping one month, i.e., MOM is the natural logarithm of the stock's gross return over the standard momentum formation period covering months $t-12$ to $t-2$ (Fama and French, 1996; Carhart, 1997). HTP is the stock's log return from the beginning of the momentum formation period to the date of the stock's highest closing price P_{high} during the momentum formation period. PTH is the stock's log return from this P_{high}-date to the end of the momentum formation period. Prices are adjusted for stock splits and dividend payments before identifying P_{high}. Hence, these definitions imply $MOM = HTP + PTH$.

To examine the relationship between these three measures and subsequent returns, we construct long-short portfolio returns WML, $rHTP$, and $rPTH$ based on MOM, HTP, and PTH, respectively. At the end of each month $t-1$, stocks are sorted into decile portfolios based on NYSE-breakpoints. The long-short returns of month t are defined as the difference between the value-weighted returns of top and bottom decile portfolio.[3] We account for delisting returns following the procedure proposed by Shumway (1997).[4]

Our sample contains all common ordinary US stocks traded on NYSE, AMEX, or NASDAQ. The sample period for the long-short returns covers January 1927 to December 2018

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

[2] CRSP and COMPUSTAT data were provided by Wharton Research Data Services.

[3] As a robustness test, we also conduct all of our analyses with long-short returns that are constructed according to the UMD momentum factor consstruction as proposed by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. The results are qualitatively the same and presented in Tables A6 to A8 and Figures A2 to A5 in the Online Appendix.

[4] The resulting monthly return time-series WML, $rHTP$, and $rPTH$ can be obtained from `https://www.wiwi.uni-muenster.de/fcm/en/the-fcm/lsf/team/hannes-mohrschladt/data`.

since CRSP data is available since January 1926 and we need twelve months of return data to calculate the main stock-level variables. Any stock-month-observation is included in our sample if these main variables of interest MOM, HTP, and PTH can be calculated, i.e., if stock return data for the previous twelve months is available. This leads to a total of 3,164,363 stock-month-observations.

3. Evidence on Momentum Crashes

3.1. Long-Short Returns of the two Momentum Components

We allocate stocks to ten decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ to obtain the respective long-short portfolio returns WML, $rHTP$, and $rPTH$ in month t. Table 1 reports summary statistics for the traditional winner-minus-loser strategy WML and for the long-short strategies $rHTP$ and $rPTH$.[5] We document a significant momentum effect of 1.21% per month. Both HTP and PTH yield significant return spreads, too, i.e., both momentum components contribute to the overall momentum phenomenon. However, the average return spread associated with HTP is 1.18% but only 0.52% for PTH. While the positive relationship between PTH and subsequent returns is qualitatively in line with George and Hwang (2004), the complementing component HTP shows substantially stronger return predictability. This observation underlines that PTH indeed contributes to momentum profits, but that large parts stem from HTP which has not received any research attention so far.

Turning to the volatility of the long-short strategies, $rPTH$ shows the highest standard deviation resulting in a comparably low Sharpe ratio of 0.21. For $rHTP$, the low standard

[5] Average returns for each of the ten decile portfolios are provided in Table A1 in the Online Appendix. It also presents both value- and equally-weighted returns as well as both raw returns and Fama and French (1993) three factor adjusted returns.

deviation contributes to its high Sharpe ratio of 0.71 – clearly exceeding the momentum Sharpe ratio of 0.54. Moreover, in contrast to $rHTP$, the long-short returns WML and $rPTH$ are negatively skewed and much more leptocurtic. This observation provides initial evidence that both MOM- and PTH-strategy induce higher tail and crash risk than the HTP-strategy. To shed more light on this, we further report the maximum drawdown of the three strategies. It is defined as the lowest hypothetical return that an investor could have achieved with the respective investment strategy. While we confirm previous literature on severe momentum crashes (maximum WML drawdown of -95.53%), we show that this property is not shared by $rPTH$ and $rHTP$ to the same extent: the maximum drawdown of $rPTH$ is -99.88%, but only -66.92% for $rHTP$. The picture is similar for the minimum monthly returns of the three long-short strategies. The minimum of $rPTH$ is the lowest (-83.40%), closely followed by the minimum of WML (-77.56%), while the minimum of $rHTP$ is much smaller in absolute terms (-32.80%). These observations directly relate to the extensive research on momentum crashes (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015). We show that a strategy on the momentum component PTH implies even more negatively skewed returns than standard momentum and higher crash risk. At the same time, upon removing PTH from MOM, the resulting HTP-strategy yields long-short returns with slightly positive skewness and substantially reduced crash risk.

To visualize the summary statistics from Table 1, Figure 1 depicts the cumulative returns of WML, $rHTP$, $rPTH$, and the excess market return MKT for the entire sample period in Panel A. From 1927 to 2018, $rHTP$ yields the highest cumulative return and outperforms the standard winner-minus-loser strategy WML. More specifically, a hypothetical $1 investment on $rHTP$ in January 1927 resulted in $72,003.84 at the end of 2018 while a corresponding WML-strategy resulted in $9,658.51 only. At first sight, it might be surprising that the

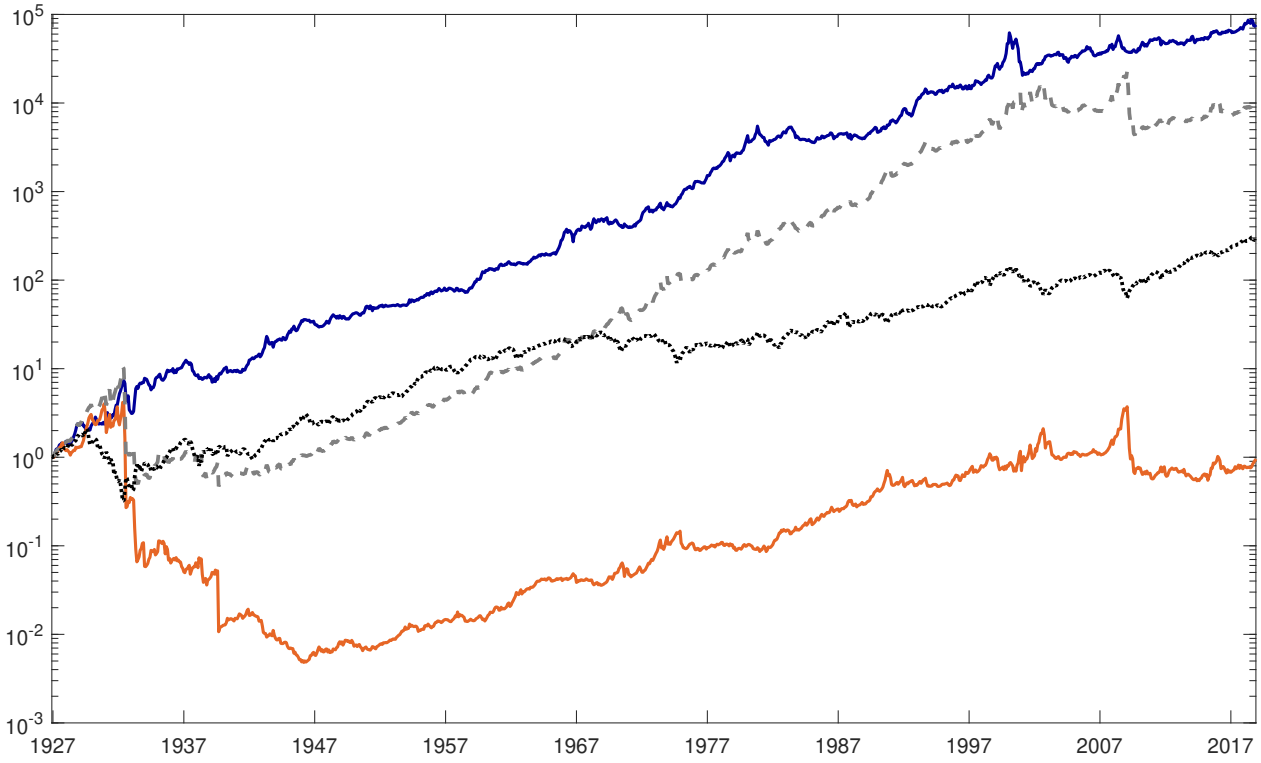
Table 1. Monthly Long-Short Returns *WML*, *rHTP*, and *rPTH*
This table displays summary statistics for the monthly long-short portfolio returns WML, $rHTP$, and $rPTH$. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 2018.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.21	5.47	7.78	0.54	-2.35	20.53	-95.53	-77.56	-1.67	1.57	4.99	25.83
$rHTP$	1.18	6.40	5.77	0.71	0.08	8.57	-66.92	-32.80	-1.65	0.92	4.27	35.22
$rPTH$	0.52	1.96	8.74	0.21	-2.70	22.97	-99.88	-83.40	-2.31	1.36	4.23	33.34

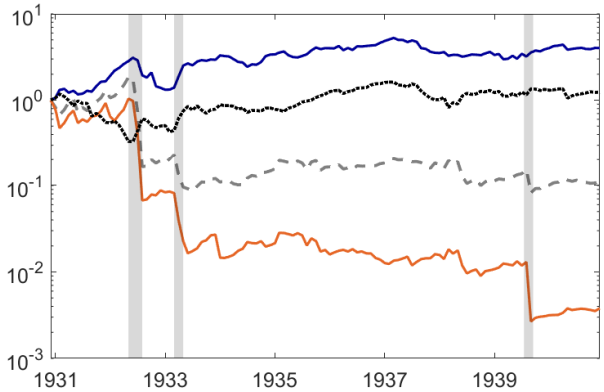
cumulative return of the HTP-strategy is much higher than that of the WML-strategy even though its mean monthly return is slightly smaller (see Table 1). The reason is that $rHTP$ does not crash severely during the sample period such that its geometric mean is higher compared to WML. This observation underlines how strongly WML is affected by crashes while $rHTP$ is not. With respect to $rPTH$, crashes have an even more severe impact on its cumulative strategy performance: a \$1 investment on $rPTH$ in 1927 results in only \$0.96 at the end of 2018. In addition, Figure 1 illustrates that both WML and $rPTH$ do not yield positive return premiums during the last ten years of our sample period due to their crashes in 2009 (on recently deteriorating momentum profitability, also see Bhattacharya et al., 2012 and Yang and Zhang, 2019). As Table A2 in the Online Appendix shows, the average monthly long-short returns WML and $rPTH$ are indeed negative from January 2009 to December 2018. However, $rHTP$ yields a significant monthly return premium of 0.60% during this period. Hence, by dropping the PTH-component from MOM, the HTP-strategy avoids the 2009 crash and allows for significant momentum profits even in recent years.

Figure 1. Cumulative Long-Short Returns
This figure shows the cumulative monthly long-short portfolio returns WML, $rHTP$, and $rPTH$. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. Hence, all portfolios are rebalanced on a monthly basis. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. In addition, this figure shows the cumulative excess market return MKT.

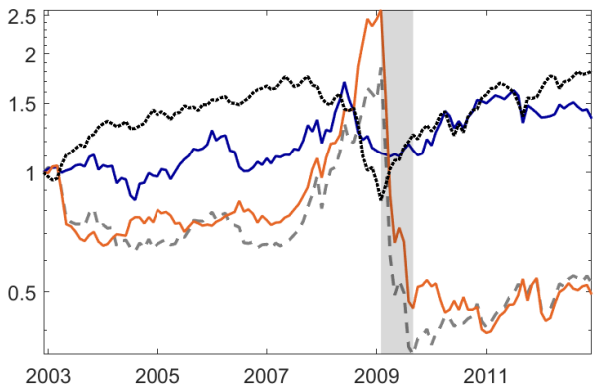
Panel A: January 1927 to December 2018



Panel B: January 1931 to December 1940



Panel C: January 2003 to December 2012



In the following, we will examine the strategies' crash properties in greater detail. To do so, we identify two major momentum crash periods, the first in the 1930s during the Great Depression and another one following the market downturn of the financial crisis in 2009. To get a better understanding of the exact movements of WML, $rHTP$, and $rPTH$ during these periods, Panels B and C from Figure 1 depict the cumulative returns during the subperiods 1931 to 1940 and 2003 to 2012 in more detail. The two subplots demonstrate that WML and $rPTH$ crash simultaneously whereas $rPTH$ crashes even more severely compared to WML.[6] Moreover, these crashes tend to occur after market downturns when the market rebounds. On the contrary, $rHTP$ shows a rather smooth progress over time and no signs of concomitant crashes. These much higher cumulative returns during the major crash periods play a large role in its overall better cumulative performance compared to WML and $rPTH$.

The overall findings from Table 1 and Figure 1 add to the vivid debate on how to reduce the crash risk of momentum trading strategies. Barroso and Santa-Clara (2015) reduce this crash risk with an alternative strategy that aims at a constant volatility, i.e, their strategy reduces the WML exposure in times of high volatility when crashes are more likely (see similar approach in Moreira and Muir, 2017). Daniel and Moskowitz (2016) use time-series methods to predict WML and its crashes. Based on these insights, they propose a dynamic momentum strategy that avoids crashes and increases the momentum strategy's Sharpe ratio. Han et al. (2016) use a simple stop-loss strategy to reduce the losses resulting from momentum crashes. While all these approaches try to avoid severe losses based on time-series predictions of momentum crashes, Chuang and Ho (2014), Yang and Zhang (2019), and Hoberg et al. (2020) eliminate specific subgroups of stocks from the construction

[6]We highlight the momentum crashes by grey bars in Panels B and C and will also show these bars in the following graphs for orientation reasons.

of momentum portfolios in order to reduce crash risk. On the contrary, our approach avoids momentum crashes without requiring time-varying investment exposure while using the full cross-section of stocks. Instead, we propose a simple cross-sectional strategy based on the momentum component HTP which allows to completely avoid negative return skewness. Hence, crashes are no inherent property of momentum strategies but can be avoided by simply eliminating the PTH-component. This observation also shows that average momentum returns cannot be completely explained as a risk premium that compensates investors for the infrequent momentum crashes: although $rHTP$ does not crash, it carries a significant return premium.

Table 2. Most Extreme Momentum Crash Months
This table shows monthly long-short portfolio returns WML, $rHTP$, and $rPTH$ for those ten months t in the sample period that show the most negative return WML. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. In addition, the table shows the market excess return of month t (MKT) as well as the cumulative market excess return of months $t-24$ to $t-1$ (MKT_{24m}). The sample period covers January 1927 to December 2018.

month	WML	$rHTP$	$rPTH$	MKT	MKT_{24m}
1932-08	-77.56	-32.80	-83.40	37.06	-68.46
1932-07	-58.25	-7.15	-58.53	33.84	-75.47
1939-09	-45.93	11.27	-79.48	16.88	-21.62
2009-04	-45.10	-1.14	-44.22	10.19	-43.51
1933-04	-43.58	35.22	-51.73	38.85	-59.65
2001-01	-41.81	-14.34	-39.56	3.13	-0.28
2009-03	-39.21	-0.81	-39.01	8.95	-47.79
1938-06	-32.49	-4.55	-33.15	23.87	-28.23
1931-06	-29.58	-9.24	-28.20	13.90	-50.52
1933-05	-27.11	33.56	-42.61	21.43	-37.76

To more closely examine momentum crashes, Table 2 presents long-short returns for the ten months with the most negative WML returns. Beyond WML, $rHTP$, and $rPTH$, Table 2 also shows the market excess return for the respective month (MKT) as well as the cumulative market excess return over the preceding 24 months (MKT_{24m}). Nine out

of the ten months were part of the Great Depression in the 1930s or the financial crisis in 2009. The only exception is January 2001 with a WML-return of -41.81% following the stock market downturn after the turn of the millenium. It is striking that for all ten months, $rHTP$ yields higher returns than WML and $rPTH$. Across these ten most severe momentum crash months, the average HTP-strategy return is even positive. On the contrary, the PTH-strategy crashes to a similar extent as WML. These figures provide additional evidence that momentum crashes occur because of the PTH-component. Upon removing PTH, the resulting amended momentum strategy based on HTP substantially alleviates crash risk.

A common feature of all ten crash months displayed in Table 2 is that the excess market return during these months is always positive while the return over the preceding 24 months is always negative. This is in line with the findings of Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) who show that WML-crashes tend to occur when the market rebounds following severe market downturns. Our results show that this observation also applies to PTH but not to HTP. We examine the strategies' market state dependence more thoroughly in the following subsection.

3.2. Market State Dependence

Closely related to momentum crashes is the literature on the market state dependence of momentum profits demonstrating that momentum strategies only yield positive returns during expansionary periods but not during recessions (Chordia and Shivakumar, 2002; Cooper et al., 2004; and Avramov and Chordia, 2006). Cooper et al. (2004) show that momentum profits only exist if the market return over the preceding three years is positive (up state). If the lagged three-year market return is negative (down state), a momentum strategy yields insignificantly negative returns. Following their procedure, we test whether

WML, $rHTP$, and $rPTH$ depend on up versus down market states. Table 3 shows that $rHTP$ is not significantly affected by the market state. It is significantly positive following both up and down market states and there is no significant difference between up and down markets. This is in line with the finding that $rHTP$ does not crash following severe market downturns. In contrast to that, WML and $rPTH$ are significantly positive following up market states and insignificantly negative following down market states. There is a significant difference for WML and $rPTH$ between up and down market states. We therefore conclude that momentum's market state dependence is driven by its PTH-component since $rHTP$ yields substantial return premiums irrespective of the market state. Stated differently, not all parts of momentum profits are market state dependent – a momentum strategy based only on its HTP-component also performs well following down market states.

Closely related to the market state is the cross-sectional dispersion in stock returns (RetDisp) as it is a strong countercyclical indicator (Loungani et al., 1990; Gomes et al., 2003; Stivers, 2003; Zhang, 2005; and Stivers and Sun, 2010). Stivers and Sun (2010) show that momentum profitability negatively depends on cross-sectional return dispersion. We examine whether this WML property is shared by $rHTP$ and $rPTH$ and present the respective average long-short returns during periods of low and high cross-sectional return dispersion in Table 3. The calculation of cross-sectional return dispersion follows Stivers and Sun (2010) and we split the sample in high and low dispersion months using the median dispersion level in our sample period. Indeed, $rPTH$ is only positive when return dispersion is low – qualitatively in line with the findings on WML. The difference between periods of low and high return dispersion is significant for both $rPTH$ and WML. On the contrary, $rHTP$ does not depend on the level of return dispersion: it generates monthly return spreads of more than 1% in both subperiods.

Table 3. Subperiod Analyses of Long-Short Returns WML, $rHTP$, and $rPTH$
This table shows average monthly long-short portfolio returns WML, $rHTP$, and $rPTH$ for different market state and return dispersion subperiods. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. Following Cooper et al. (2004), the up (down) market state subperiod includes all months t for which the market return over months $t-36$ to $t-1$ is positive (negative). Following Stivers and Sun (2010), for each month, return dispersion is measured as the cross-sectional return standard deviation of 100 size/book-to-market portfolios (obtained from Kenneth R. French's homepage). Each month t is considered as high (low) return dispersion month if the average return dispersion of months $t-3$ to $t-1$ is above (below) the time-series median. The t-statistics in parentheses refer to the subperiod average returns of WML, $rHTP$, and $rPTH$ and are based on standard errors following Newey and West (1987) using twelve lags. Δ refers to the difference between the two respective subperiods. The corresponding t-statistics are based on two-sample t-tests (Welch's t-test with unequal variances). The sample period covers January 1927 to December 2018.

	WML				$rHTP$				$rPTH$			
	MktState		RetDisp		MktState		RetDisp		MktState		RetDisp	
	Up	Down	Low	High	Up	Down	Low	High	Up	Down	Low	High
mean	1.44	-0.52	1.74	0.68	1.02	1.73	1.14	1.23	0.87	-1.79	1.31	-0.27
t	(7.66)	(-0.50)	(8.30)	(1.63)	(5.29)	(2.71)	(5.86)	(3.70)	(4.29)	(-1.41)	(6.01)	(-0.55)
Δ	1.96		1.06		-0.71		-0.09		2.67		1.59	
t	(2.11)		(2.42)		(-1.20)		(-0.24)		(2.38)		(3.13)	

The overall empirical results in this section reveal substantial differences between HTP-strategy on the one hand and MOM- and PTH-strategy on the other hand. While $rPTH$ shares many characteristics with the standard WML-strategy and behaves similarly with respect to crashes and market state dependence, the HTP-strategy yields returns that are less volatile and not market state dependent. In particular, $rHTP$ does not crash, i.e., the long-short returns are positively rather than negatively skewed. We will investigate the underlying mechanisms for this different behavior in the following section.

4. Drivers of Momentum Crashes

In this section, we explore the underlying mechanisms for the different crash properties of $rHTP$ and $rPTH$ as documented in the previous section. Referring to the construction of the underlying variables HTP and PTH, two key properties are relevant here. First, PTH reflects the stock price development between P_{high} (highest stock price during months $t-12$ to $t-2$) and the stock price at the end of month $t-2$. Hence, PTH cannot be positive by construction and thus tends to reflect the negative returns of loser stocks. For HTP, this is the other way round: it cannot be negative as it measures the stock return leading up to P_{high}. Second, PTH always reflects more recent stock price movements compared to HTP. Combining these two observations, the construction of PTH-portfolios should strongly depend on the performance of recent loser stocks while the construction of HTP-portfolios should not. In this context, Daniel and Moskowitz (2016) show that momentum crashes are primarily driven by the extremely high returns of recent loser stocks in the short leg of the momentum strategy. After severe market downturns, the most extreme losers tend to rebound strongest when the market recovers – implying a negative market beta of WML during these periods. We therefore conjecture that $rHTP$ avoids momentum crashes because its construction is not based on recent losers such that $rHTP$ does not suffer from a severe negative market risk exposure when the market recovers after downturns. We investigate these arguments empirically in the following two subsections.

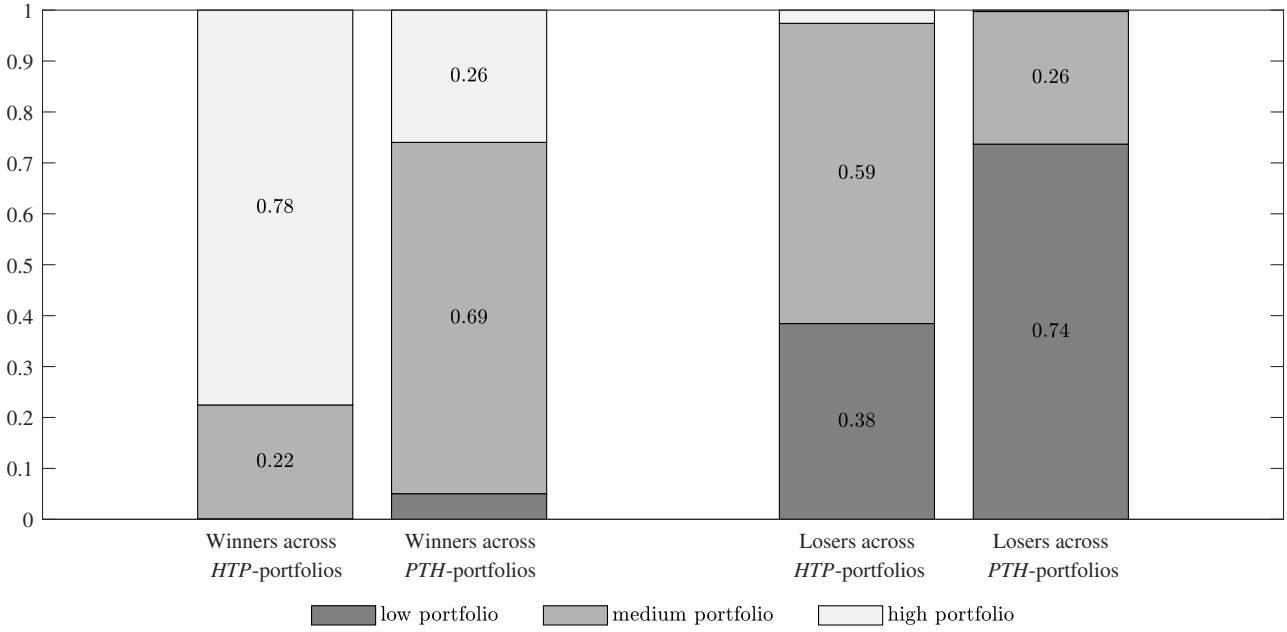
4.1. Loser Stocks

Daniel and Moskowitz (2016) show that momentum crashes are driven by the loser stocks in the bottom MOM-decile. We therefore examine to which extent winner and loser stocks

also show up in the extreme HTP- and PTH-deciles. Figure 2 shows the location of these winner and loser stocks across top-, bottom-, and medium-HTP (PTH) decile portfolios, i.e., it shows whether the winners and losers show up in the HTP (PTH) strategy's long leg, short leg, or none of the two legs. For example, the first bar in Figure 2 shows that 78% of winner stocks are also in the top-HTP portfolio, i.e. 78% of stocks in the top-MOM decile are also part of the top-HTP decile. In contrast, only 26% of winner stocks also belong to the top-PTH portfolio. In line with the construction of HTP and PTH, this result suggests that winner stocks contribute more to the long leg of the HTP-strategy than to the long leg of the PTH-strategy. This picture looks different for loser stocks: only 38% of loser stocks are part of the bottom-HTP portfolio while 74% of loser stocks belong to the bottom-PTH portfolio. Thus, loser stocks strongly influence the short leg of the PTH-strategy and less so the short leg of the HTP-strategy. To the extent that momentum crashes are due to these loser stocks, Figure 2 provides initial evidence why $rPTH$ crashes more severely than $rHTP$.

The asymmetry in Figure 2 suggests that $rHTP$ rather reflects the long leg of WML while $rPTH$ tends to reflect the (crash-prone) WML short leg. We directly test this implication in Table 4. It presents correlation coefficients for WML, long as well as short leg-based WML, $rHTP$, and $rPTH$. We define the long leg-based return WML_{LL} as the return difference between value-weighted returns of the top-MOM decile and the mean of value-weighted returns of the second to ninth MOM-decile. Equivalently, the short leg-based return WML_{SL} is the return difference between the mean of value-weighted returns of the second to ninth MOM-decile and the value-weighted returns of the bottom-MOM decile. This methodology implies that WML is split up into its long and short leg component such that $WML = WML_{LL} + WML_{SL}$.

Figure 2. Winner and Loser Stocks in Long and Short Leg of *HTP*- and *PTH*-Strategies
The two bars on the left show the time-series average proportion of winner stocks assigned to different HTP-portfolios (PTH-portfolios). The two bars on the right show the time-series average proportion of loser stocks assigned to different HTP-portfolios (PTH-portfolios). For each month t, winner (loser) stocks are identified as the stocks in the highest (lowest) MOM-decile. The bars show the proportion of these stocks that are simultaneously identified as low- (bottom decile), medium- (deciles two to nine), or high- (top decile) HTP (PTH). MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The sample period covers January 1927 to December 2018.



As expected, both $rHTP$ and $rPTH$ show a significantly positive correlation with WML as the underlying variables HTP, PTH, and MOM are linearly related by construction. Notably, the correlation between $rPTH$ and WML is considerably higher than that of $rHTP$ and WML. This is consistent with the graphical evidence in Figure 1 which illustrates that WML and $rPTH$ crash simultaneously.[7] Further, the correlation between WML_{LL} and $rHTP$ is 68% while the correlation between WML_{LL} and $rPTH$ is only 34%. This observation is in line with the evidence from Figure 2 that winner stocks (which contribute

[7]By construction, the correlation coefficients are most strongly affected by the most extreme returns. Supporting this argument, if we merely disregard the ten most severe momentum crash months (Table 2) from our 1,104-month sample, the WML-$rPTH$-correlation already drops to 0.68 while the WML-$rHTP$-correlation increases to 0.46 (see Table A4 in the Online Appendix).

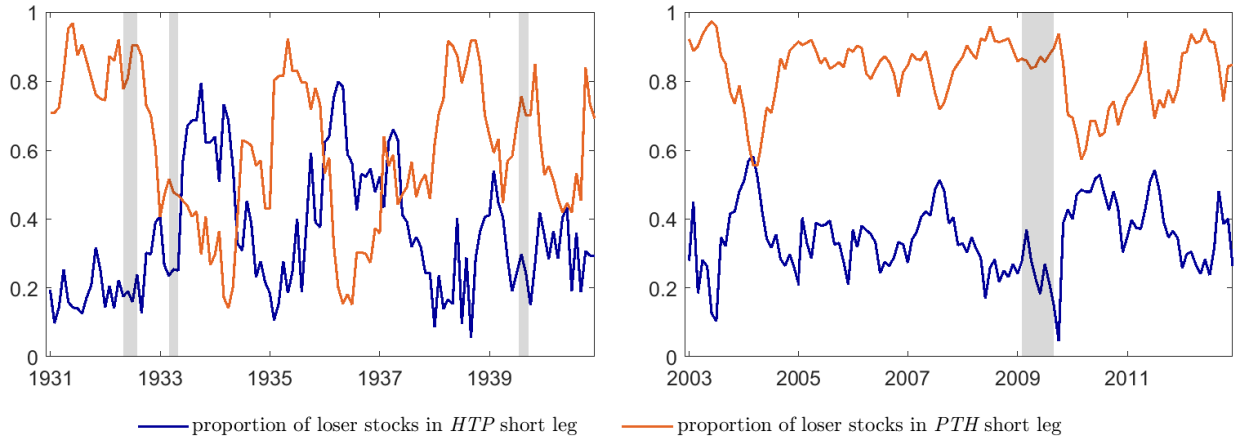
to WML_{LL}) influence the HTP- rather than the PTH-strategy's long leg. For WML_{SL} the picture is reversed: the correlation between WML_{SL} and $rHTP$ is only 2% while it is 87% between WML_{SL} and $rPTH$. Hence, Table 4 provides additional evidence that the short leg of momentum is strongly related to $rPTH$ but not to $rHTP$. Stated differently, $rHTP$ avoids severe momentum crashes as it is largely unaffected by the return movements of loser stocks in the momentum strategy's short leg.

Table 4. Correlation of WML, WML_{LL}, WML_{SL}, $rHTP$, and $rPTH$
This table displays the return correlation coefficients for monthly WML, long leg-based WML, short leg-based WML, $rHTP$, and $rPTH$. For each month t, WML is the value-weighted return difference between top- and bottom-MOM decile. WML_{LL} is the value-weighted return difference between top-MOM decile and medium-MOM deciles (average return of deciles two to nine). WML_{SL} is the value-weighted return difference between medium-MOM deciles (average return of deciles two to nine) and bottom-MOM decile. $rHTP$ ($rPTH$) is the value-weighted return difference between top-HTP (PTH) and bottom-HTP (PTH) decile portfolios. Stocks are allocated to these decile portfolios at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The t-statistics for correlation coefficients are shown in the right part of the table. The sample period covers January 1927 to December 2018.

	Correlation Coefficient					t-statistics				
	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$
WML	1.00									
WML_{LL}	0.76	1.00				38.87				
WML_{SL}	0.86	0.32	1.00			55.73	11.25			
$rHTP$	0.38	0.68	0.02	1.00		13.74	30.83	0.71		
$rPTH$	0.78	0.34	0.87	-0.11	1.00	41.64	12.16	58.40	-3.66	

Figure 2 links loser stocks to the short leg of the PTH-strategy. The different prevalence of loser stocks in the PTH versus HTP strategy's short leg could rationalize why $rPTH$ crashes while $rHTP$ does not. However, while Figure 2 reports mean values for the entire sample period, our arguments require a closer look at the relevant crash periods. Therefore, Figure 3 depicts the fraction of loser stocks that are part of the bottom-HTP (bottom-PTH) portfolio for the two major crash periods. For example, the HTP-graph in Figure 3 shows how the average proportion of 0.38 (see Figure 2) varies across time.

Figure 3. Loser Stocks in Short Leg of *HTP*- and *PTH*-Strategies
This figure shows the proportion of loser stocks assigned to the bottom-HTP decile (bottom-PTH decile) across time. For each month t, loser stocks are identified as the stocks in the lowest MOM decile. The graphs show the proportion of these stocks that are simultaneously identified as low-HTP (low-PTH) stocks. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.



The momentum crashes (see grey bars in Figure 3) result from the high returns of loser stocks in the momentum strategy's short leg (Daniel and Moskowitz, 2016). Figure 3 shows that the proportion of loser stocks in the PTH short leg is considerably larger than in the HTP short leg then. Hence, coinciding with the momentum crashes, the high returns of loser stocks imply particularly negative returns for the PTH-strategy but not for the HTP-strategy. Hence, by eliminating PTH from MOM, long-short returns based on the remaining HTP-component suffer less from the temporary adverse impact of loser stocks.

4.2. Time Varying Market Betas and Optionality

According to Daniel and Moskowitz (2016), loser stocks contribute to WML crashes via the following mechanism: after market drawdowns, the equity of the most extreme loser firms resembles an out-of-the-money call option on the firm value. Hence, these loser

stocks perform exceptionally well when the market recovers. As these loser stocks are in the momentum strategy's short leg, WML behaves like a written call option on the market: if the market return is positive, WML shows strong negative returns; if the market return is negative, WML shows mild positive returns. Stated differently, there is a negative and concave dependence of WML on MKT such that WML crashes when the market rebounds. We therefore examine to which extent differences in these optionality characteristics can explain why $rPTH$ crashes while $rHTP$ does not. To do so, Table 5 presents regression coefficients for the time-series regression

$$WML_t = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t \tag{2}$$

following Daniel and Moskowitz (2016). Beside examining WML, we also run this regression using $rHTP$ and $rPTH$ as the dependent variable. The bear market indicator B_t equals one if the cumulative market return in months $t-24$ to $t-1$ is negative and zero otherwise. R_t serves as an indicator for market rebounds and equals one if the excess market return in month t is positive and zero otherwise.

Regression specification (1) in Table 5 shows that all three strategies WML, $rHTP$, and $rPTH$ yield significant return premiums after accounting for market risk. The negative market beta of WML is in line with Daniel and Moskowitz (2016). Moreover, the long-short strategy based on HTP has a positive market beta of 0.36 (t=3.39) while the long-short strategy based on PTH has a negative market beta of -1.01 (t=-8.98). These differences can be rationalized by the construction of HTP and PTH. Stocks with a high market beta tend to outperform during up markets. As HTP measures the strength of a stock's up movement that leads to P_{high}, high-HTP stocks have higher market betas on average. On the contrary,

PTH measures a stock's down movement after P_{high} such that stocks in the PTH short leg tend to have comparably high market betas.

Regression specification (2) provides two major insights. First, all three long-short strategies provide significantly positive market-adjusted returns in bull markets (α_0). However, in bear markets, the alphas of WML and $rPTH$ decline by 1.73% (t=-2.56) and 2.37% (t=-2.86), respectively, and thus turn negative. In line with Table 3, only $rHTP$ does not provide lower returns during bear markets. Second, the market betas of $rHTP$, $rPTH$, and WML are significantly lower in bear than in bull markets. However, while the $rHTP$ market beta remains positive even in bear markets, $rPTH$ shows a strong negative market risk exposure during bear markets (market beta of -1.41).

Turning to regression specification (3), the findings with respect to WML are in line with Daniel and Moskowitz (2016): the WML market beta is negative in bear markets and even more so when the market rebounds, i.e., when the value-weighted market excess return is positive. Hence, WML behaves like a written call option on the market. This interpretation also applies to $rPTH$; the negative market risk exposure is even more pronounced: during market rebounds in bear periods, $rPTH$ shows a negative market beta of -1.79. Hence, the overall negative market risk exposure of $rPTH$ is even more negative during bear markets and market rebounds explaining the severe $rPTH$ crashes. On the contrary, the market beta of $rHTP$ remains positive when the market recovers from bear markets. In none of the three regression specifications, $rHTP$ exhibits a negative market beta which points out that the long-short strategy based on HTP does not show option-like behavior with respect to the market.

Overall, the results provided in Table 5 suggest that long-short investment strategies based on MOM and PTH are comparable to shorting a call option on the market since

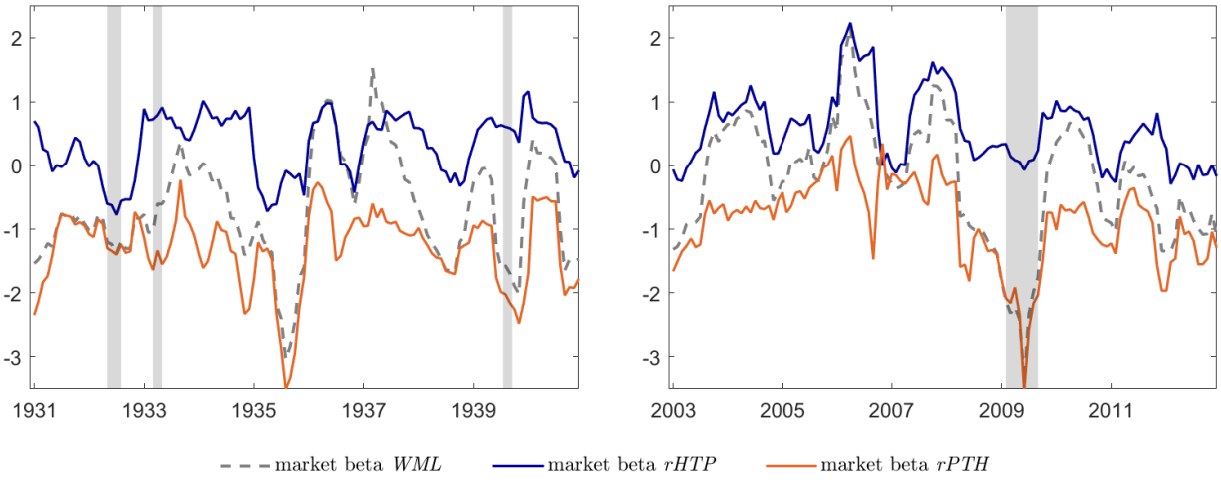
Table 5. Time Varying Market Betas and Optionality of *WML*, *rHTP*, and *rPTH*
This table shows regression coefficients for the time-series regression $WML_t = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t$. In alternative specifications, $rHTP$ and $rPTH$ are used as dependent variables instead of WML. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MKT_t is the excess market return in month t. B_t is a bear market dummy which equals one if the market return over months $t-24$ to $t-1$ is negative and zero otherwise. R_t is a rebound dummy which equals one if the excess market return in month t is positive and zero otherwise. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers January 1927 to December 2018.

	WML			$rHTP$			$rPTH$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
α_0	1.55	1.57	1.57	0.95	0.71	0.71	1.17	1.38	1.38
	(8.67)	(8.71)	(8.70)	(4.90)	(3.87)	(3.87)	(6.23)	(7.77)	(7.76)
α_B		-1.73	0.70		0.75	0.47		-2.37	0.54
		(-2.56)	(0.77)		(1.32)	(0.39)		(-2.86)	(0.67)
β_0	-0.53	-0.02	-0.02	0.36	0.55	0.55	-1.01	-0.66	-0.66
	(-3.37)	(-0.32)	(-0.32)	(3.39)	(8.58)	(8.58)	(-8.98)	(-9.35)	(-9.34)
β_B		-1.10	-0.65		-0.42	-0.47		-0.75	-0.22
		(-6.90)	(-4.74)		(-2.27)	(-3.62)		(-5.49)	(-1.81)
$\beta_{B,R}$			-0.76			0.09			-0.91
			(-3.28)			(0.24)			(-4.51)

the betas of WML and $rPTH$ are extremely low when the market recovers from periods of negative market returns. The negative betas of WML and $rPTH$ in these situations imply severely negative returns when the market is in a sharp up movement. On the contrary, a long-short investment strategy based on HTP does not show this optionality characteristic as the beta of $rHTP$ is positive when the market recovers from bear market periods. Hence, in line with our evidence in the previous Section, $rHTP$ does not crash.

Supplementing Table 5, Figure 4 depicts time-series fluctuations in the strategies' market risk exposure. More specifically, it depicts 6-month rolling market betas of WML, $rHTP$, and $rPTH$ for the two major crash periods. Figure 4 shows that the market betas of WML, $rHTP$, and $rPTH$ vary substantially across time. With respect to WML, this variation is also thoroughly documented by Grundy and Martin (2001) who find a particularly negative

Figure 4. Rolling Market Betas of *WML*, *rHTP*, and *rPTH*
This figure shows rolling market betas for daily long-short portfolio returns WML, $rHTP$, and $rPTH$. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. Market betas are based on six-month rolling windows of daily returns and take into account ten daily lags for the market return. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.



market risk exposure of WML following market downturns. We show that this variation also extends to $rHTP$ and $rPTH$.

In line with the regression estimates in Table 5, the market beta of $rHTP$ tends to be above zero most of the time and does not become consistently negative during the momentum crash months. Referring to $rPTH$, its market beta is largely below zero and drops even further during the most extreme momentum crashes. These findings help to further understand why WML and $rPTH$ crash while $rHTP$ does not: the market betas of WML and $rPTH$ are severely negative in bear markets when the market rebounds. As these rebound months have a positive market return by definition, this implies the crash-like returns of WML and $rPTH$.

Concluding this section, $rHTP$ avoids the typical momentum crashes via the following mechanism: eliminating PTH from MOM implies that HTP does not reflect recent loser performance by construction. Consequently and in contrast to MOM and PTH, after market downturns, the HTP short leg does not behave like an out-of-the-money call option on the market. Hence, $rHTP$ has no negative market beta when the market rebounds such that it avoids the typical momentum crashes.

5. Cross-Sectional Analysis of MOM, HTP, and PTH

So far, our analyses focus on the time-series properties of $rHTP$ and $rPTH$. In the previous section, we document substantial crashes of $rPTH$ in contrast to $rHTP$. At the same time, Table 1 shows that both $rPTH$ and $rHTP$ carry significantly positive monthly return premiums. In this section, we examine how the underlying momentum components PTH and HTP shape the overall momentum phenomenon in the cross-section of stock returns. From an econometric perspective, the cross-sectional contribution of the two components to the momentum effect can be easily illustrated with the following argument. Consider the cross-sectional OLS regressions (1) $R_t = \alpha_1 + \gamma_{MOM} MOM_{t-1} + \epsilon_{1,t}$, (2) $R_t = \alpha_2 + \gamma_{HTP} HTP_{t-1} + \epsilon_{2,t}$, and (3) $R_t = \alpha_3 + \gamma_{PTH} PTH_{t-1} + \epsilon_{3,t}$. Then, $MOM_{t-1} = HTP_{t-1} + PTH_{t-1}$ implies the following relationship between the three regression slope coefficients:

$$\hat{\gamma}_{MOM} = \frac{\sigma^2_{HTP}}{\sigma^2_{MOM}} \hat{\gamma}_{HTP} + \frac{\sigma^2_{PTH}}{\sigma^2_{MOM}} \hat{\gamma}_{PTH} \tag{3}$$

where σ_{MOM}, σ_{HTP}, and σ_{PTH} denote the cross-sectional standard deviation of MOM, HTP, and PTH, respectively. Equation (3) shows that $\hat{\gamma}_{MOM}$ is a linear combination of $\hat{\gamma}_{HTP}$

and $\hat{\gamma}_{PTH}$. More specifically, $\hat{\gamma}_{MOM}$ can be interpreted as the variance-weighted average of $\hat{\gamma}_{HTP}$ and $\hat{\gamma}_{PTH}$. Thus, the cross-sectional momentum effect as reflected by $\hat{\gamma}_{MOM}$ is fully spanned by the non-crashing component $\hat{\gamma}_{HTP}$ and the crash-affected component $\hat{\gamma}_{PTH}$. Moreover, Equation (3) allows us to investigate to which extent HTP and PTH contribute to the momentum effect across time. In the following two subsections, we examine these cross-sectional relationships empirically.

5.1. MOM, HTP, and PTH in Cross-Sectional Regressions

To investigate the relationship between MOM, HTP, PTH, and subsequent returns, we first run cross-sectional regressions following Fama and MacBeth (1973). The regression analyses also allow us to test whether the return predictability associated with MOM, HTP, and PTH is subsumed by standard control variables. Regression specifications (1) to (3) in Table 6 show that MOM as well as both HTP and PTH positively predict one-month-ahead stock returns with high statistical significance. The return predictability of HTP and PTH remains significant when we control for a stocks's market beta ($BETA$), firm size ($SIZE$), book-to-market ratio (BM), Amihud (2002) illiquidity ($ILLIQ$), the stock return in the previous month (REV), and idiosyncratic return volatility ($IVOL$). Noteworthy, the coefficient magnitude of HTP is slightly higher than that of PTH in regression specification (4), but is slightly lower in regression specifications (5) and (6) when adding control variables. Hence, neither HTP nor PTH can be considered as the clearly dominant component with respect to explaining momentum profits.[8] This observation thus reinforces our argument

[8]Note that these regression analyses indicate similar return predictive power for HTP and PTH whereas the mean of $rPTH$ is considerably higher than the mean of $rHTP$ (see Table 1). The reason is that the Fama-MacBeth-regressions in Table 6 apply *equally*-weighted OLS regressions while $rPTH$ and $rHTP$ are based on *value*-weighted portfolios. Table A5 in the Online Appendix presents value-weighted Fama-MacBeth-regressions: the resulting regression coefficients are consistently larger for HTP compared to PTH.

that HTP plays a substantial role for understanding momentum although previous research has exclusively focused on the return predictability associated with PTH (George and Hwang, 2004).

Table 6. *MOM*, *HTP*, and *PTH* in Fama-MacBeth-Regressions
This table reports time-series averages of monthly estimates from cross-sectional OLS regressions. The dependent variable is the stock return of month t. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. $BETA$ is the market beta defined as in Hou et al. (2020) based on daily returns of month $t-1$ including one market lead and lag return. $SIZE$ is the log market capitalization at the end of month $t-1$ and BM the book-to-market ratio based on the firms's market capitalization at the end of month $t-1$ and the book equity which is updated at the end of each June based on annual accounting data from the preceding calendar year following Fama and French (1993). $ILLIQ$ denotes stock illiquidity following Amihud (2002), REV the stock return in month $t-1$, $IVOL$ the annualized idiosyncratic return volatility of daily returns in month $t-1$ relative to the three-factor model of Fama and French (1993) as introduced by Ang et al. (2006), and $IMOM$ the log intermediate momentum return from months $t-12$ to $t-7$ as in Novy-Marx (2012).The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers January 1927 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
intercept	1.01	0.77	1.24	0.87	3.83	3.44	3.58
	(4.74)	(3.84)	(6.88)	(5.23)	(6.36)	(6.04)	(6.25)
MOM	0.97						
	(6.51)						
HTP		1.36		1.22	1.08	1.18	0.98
		(7.24)		(7.04)	(7.18)	(7.79)	(4.34)
PTH			0.82	0.90	1.63	1.35	1.30
			(2.37)	(2.80)	(6.59)	(5.75)	(5.16)
BETA					-0.03	-0.00	0.01
					(-0.97)	(-0.04)	(0.24)
SIZE					-0.16	-0.13	-0.14
					(-5.57)	(-4.96)	(-5.13)
BM					0.13	0.09	0.09
					(5.36)	(4.26)	(4.25)
ILLIQ						0.02	0.02
						(3.43)	(3.51)
REV						-0.06	-0.06
						(-13.22)	(-13.15)
IVOL						-0.79	-0.79
						(-4.58)	(-4.66)
IMOM							0.31
							(1.41)

As final control variable, regression specification (7) considers the log intermediate momentum return from months $t-12$ to $t-7$ ($IMOM$) as proposed by Novy-Marx (2012).

Novy-Marx (2012) also decomposes the total momentum formation period (months $t-12$ to $t-2$) and shows that momentum profits largely stem from months $t-12$ to $t-7$. $IMOM$ might thus be closely related to HTP which also measures a stock's return over the beginning of the momentum formation period. However, while Novy-Marx (2012) uses a fixed point in time to split up MOM, our decomposition approach is dynamic in the sense that it depends on the timing of P_{high}. Table 6 shows that the return predictability of HTP and PTH is not captured by the intermediate momentum return $IMOM$. It is even the other way round: in untabulated regressions, we find that $IMOM$ is a significantly positive return predictor if we drop HTP as explanatory variable. But with HTP, Table 6 shows that the $IMOM$-coefficient is insignificant. As additional robustness check, Table A3 in the Online Appendix examines long-short returns based on $IMOM$, complementary to Table 1. While $IMOM$ is a significant return predictor, the corresponding return spread is slightly smaller compared to HTP. More importantly, the $IMOM$-based long-short strategy yields negatively skewed returns and is prone to severe crash risk (e.g., minimum monthly return of -90.65% compared to -32.80% for $rHTP$). Consequently, in line with our arguments in Section 4, it is the dynamic MOM formation period decomposition based on P_{high} that allows $rHTP$ to alleviate momentum crash risk.

5.2. Contribution of HTP and PTH to Momentum Effect

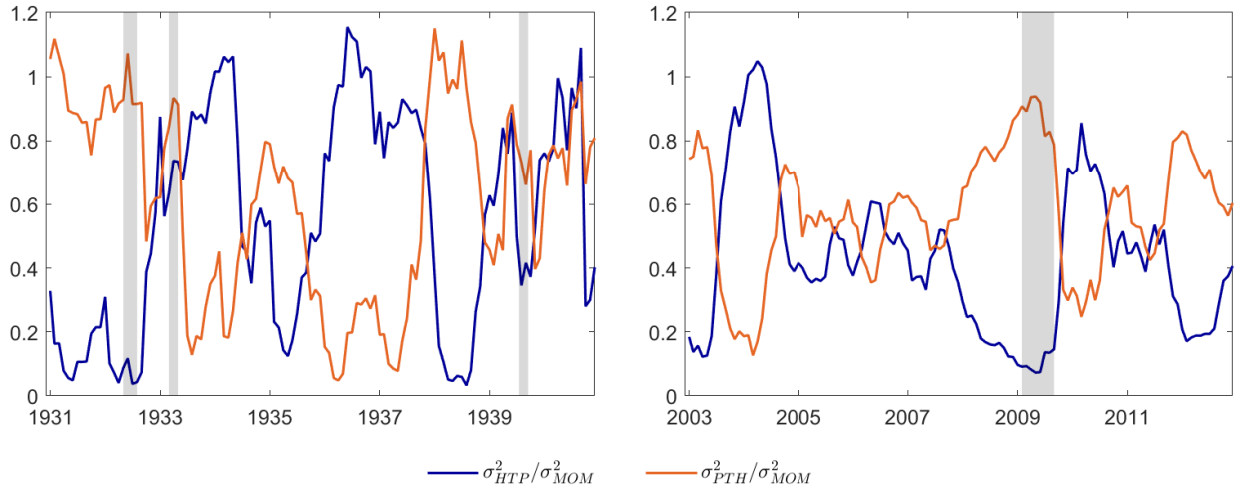
The regressions in the previous subsection suggest that HTP and PTH contribute to the overall momentum effect to a similar extent. In addition, Section 3 provides evidence that the long-short returns associated with PTH are prone to severe crashes while those associated with HTP are not. This raises the question why the momentum long-short strategy is prone to similar crashes as $rPTH$ although MOM is based on both HTP and PTH by

construction. In order to answer this question, we investigate the relative importance of HTP versus PTH for the momentum effect during the two major crash periods in the following. Referring to Equation (3), the relative importance of $\hat{\gamma}_{HTP}$ and $\hat{\gamma}_{PTH}$ for the momentum effect $\hat{\gamma}_{MOM}$ is given by the weights $\sigma^2_{HTP}/\sigma^2_{MOM}$ and $\sigma^2_{PTH}/\sigma^2_{MOM}$, respectively. During the overall sample period, $\hat{\gamma}_{HTP}$ and $\hat{\gamma}_{PTH}$ contribute to $\hat{\gamma}_{MOM}$ to a similar extent: the time-series averages of $\sigma^2_{HTP}/\sigma^2_{MOM}$ and $\sigma^2_{PTH}/\sigma^2_{MOM}$ are 0.5038 and 0.5028, respectively. However, these weights are subject to substantial variation across time. Figure 5 depicts the weights for the two major crash periods. During the momentum crash months (grey bars), $\hat{\gamma}_{MOM}$ disproportionately depends on $\hat{\gamma}_{PTH}$ as opposed to $\hat{\gamma}_{HTP}$. For example, during the most recent momentum crash in 2009, $\sigma^2_{HTP}/\sigma^2_{MOM}$ is around 0.1 while $\sigma^2_{PTH}/\sigma^2_{MOM}$ is around 0.9. This implies that the momentum effect is almost exclusively determined by the PTH-component then. Hence, as $rPTH$ crashes, WML crashes as well and does not benefit from the crash-resilient nature of $rHTP$.

The high value of $\sigma^2_{PTH}/\sigma^2_{MOM}$ during crash periods can be traced back to two sources. First, as the crash periods follow market downturns, a comparably large proportion of the momentum formation period belongs to PTH rather than HTP as the former measures a stock's price decline following P_{high}.[9] Second, as PTH directly reflects the market downturns, it is far more volatile than HTP during the crash periods. These two factors contribute to high weights $\sigma^2_{PTH}/\sigma^2_{MOM}$ when $rPTH$ crashes such that WML crashes as well. Hence, our analyses allow to trace back momentum crashes to the MOM-component PTH rather than HTP. Vice versa, the elimination of PTH from MOM allows to substantially reduce crash risk.

[9]The proportion of the MOM formation period which is covered by HTP versus PTH is plotted in Figure A1 in the Online Appendix: during crash months, the formation period proportion covered by PTH is higher than the proportion covered by HTP.

Figure 5. *HTP*- and *PTH*-Weights for the Momentum Effect
This figure depicts the weights $\sigma^2_{HTP}/\sigma^2_{MOM}$ and $\sigma^2_{PTH}/\sigma^2_{MOM}$ as introduced in Equation (3) which determine the contribution of $\hat{\gamma}_{HTP}$ and $\hat{\gamma}_{PTH}$ to the momentum effect $\hat{\gamma}_{MOM}$, respectively. For each month, σ^2_{HTP}, σ^2_{PTH}, and σ^2_{MOM} are the cross-sectional variances of HTP, PTH, and MOM, respectively. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.



6. Conclusion

We split up the standard momentum return over months $t-12$ to $t-2$ at the highest stock price within this formation period to decompose momentum into its two components HTP and PTH. We show that both HTP and PTH positively predict the cross-section of stock returns but that only PTH causes the well-known momentum crashes. By removing PTH from MOM, the remaining HTP-component induces long-short returns that are unskewed and not dependent on market states. HTP therefore serves as a crash-free and market state-independent alternative to momentum that yields a similar average long-short return and an even higher Sharpe ratio. These findings challenge existing theories for the profitability of momentum that rely on momentum's crash property or its market state

dependence. Hence, while economic mechanisms related to the PTH-component have been extensively studied in the 52-week high literature, the driving forces of the HTP-induced return predictability require further investigation.

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Online Appendix for

"Decomposing Momentum: Eliminating its Crash Component"

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Figure A1. Proportion of Momentum Formation Period Covered by *HTP* and *PTH*
This figure shows the proportion of the momentum formation period covered by HTP and PTH on a monthly basis. The momentum formation period from month $t-12$ to month $t-2$ is split into the HTP formation period, from month $t-12$ to the date of P_{high}, and the PTH formation period, from the date of P_{high} to month $t-2$. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.

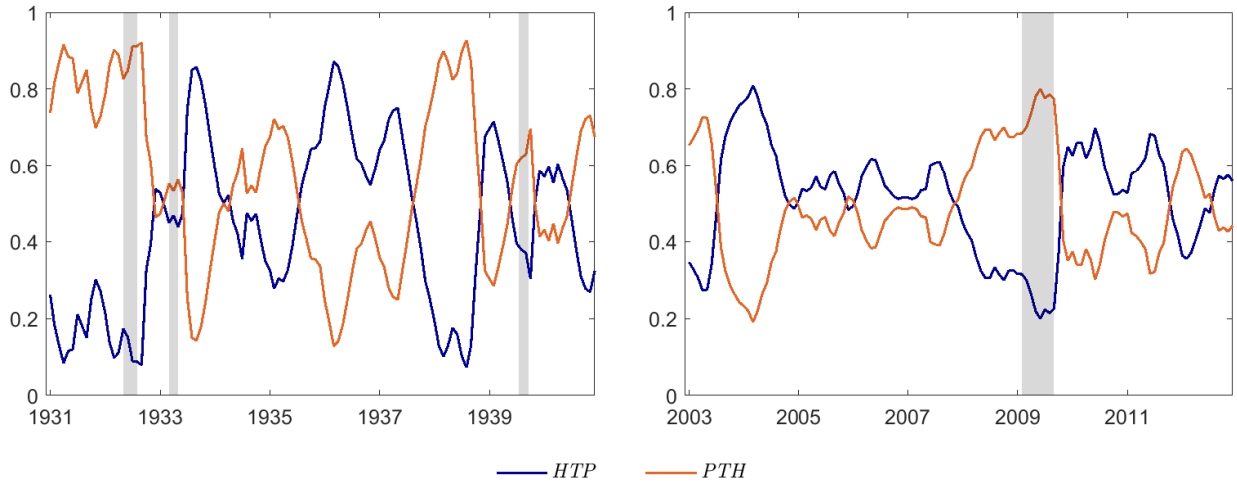


Table A1. Decile Portfolio Sorts Based on *MOM*, *HTP* and *PTH*
This table reports monthly value- and equally-weighted portfolio sorts based on MOM, HTP, and PTH. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. At the end of each month, each stock is allocated to one decile portfolio based on MOM, HTP, or PTH. Portfolio sorts are based on NYSE-breakpoints. For the subsequent month t, this table presents raw returns as well as portfolio alphas accounting for the three Fama and French (1993) factors. 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 sample period covers January 1927 to December 2018.

	MOM				*HTP*				*PTH*			
	value		equal		value		equal		value		equal	
	raw	α	raw	α	raw	α	raw	α	raw	α	raw	α
low	0.30	-1.14	0.91	-0.70	0.43	-0.48	0.60	-0.57	0.49	-1.12	1.20	-0.53
2	0.70	-0.56	1.08	-0.36	0.69	-0.19	0.79	-0.34	0.76	-0.68	1.23	-0.36
3	0.74	-0.38	1.09	-0.22	0.79	-0.13	1.02	-0.14	0.94	-0.36	1.32	-0.11
4	0.87	-0.17	1.21	-0.08	0.86	-0.06	1.12	-0.07	1.02	-0.14	1.38	0.06
5	0.89	-0.11	1.21	0.01	1.03	0.07	1.22	-0.00	1.06	-0.04	1.36	0.11
6	0.92	-0.06	1.30	0.15	1.02	0.03	1.28	0.07	0.95	-0.09	1.37	0.23
7	1.00	0.10	1.33	0.22	1.10	0.11	1.40	0.14	1.00	0.03	1.39	0.32
8	1.12	0.24	1.43	0.36	1.18	0.16	1.43	0.17	1.03	0.16	1.35	0.35
9	1.18	0.30	1.55	0.50	1.32	0.26	1.69	0.34	0.96	0.15	1.31	0.41
high	1.50	0.62	1.77	0.70	1.62	0.51	1.85	0.47	1.01	0.29	1.39	0.57
10-1	1.21	1.77	0.86	1.39	1.18	0.99	1.25	1.03	0.52	1.41	0.19	1.10
t(10-1)	(5.47)	(9.62)	(3.86)	(7.83)	(6.40)	(5.53)	(7.28)	(6.78)	(1.96)	(8.58)	(0.63)	(5.87)

Table A2. Monthly Long-Short Returns *WML*, *rHTP*, and *rPTH* from January 2009 to December 2018

This table displays summary statistics for the monthly long-short portfolio returns WML, $rHTP$, and $rPTH$. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 2009 to December 2018.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	-0.15	-0.16	8.67	-0.06	-2.09	11.75	-81.18	-45.10	-3.24	0.54	4.09	20.46
$rHTP$	0.60	2.10	4.34	0.48	-0.14	4.13	-17.32	-14.72	-1.99	0.22	2.90	11.28
$rPTH$	-0.58	-0.55	8.96	-0.22	-1.97	9.87	-85.42	-44.22	-3.85	1.06	4.34	19.50

Table A3. Monthly Long-Short Returns WML, $WML_{t-12,t-7}$, and $WML_{t-6,t-2}$
This table displays summary statistics for the monthly long-short portfolio returns WML, $WML_{t-12,t-7}$, and $WML_{t-6,t-2}$. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on MOM, $MOM_{t-12,t-7}$ (i.e., $IMOM$), and $MOM_{t-6,t-2}$ at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. $MOM_{t-12,t-7}$ is the stock's intermediate log return over formation months $t-12$ to $t-7$ and $MOM_{t-6,t-2}$ is the stock's recent log return over formation months $t-6$ to $t-2$. This formation period split follows Novy-Marx (2012). The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 2018.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.21	5.47	7.78	0.54	-2.35	20.53	-95.53	-77.56	-1.67	1.57	4.99	25.83
$WML_{t-12,t-7}$	1.08	5.41	6.65	0.56	-3.61	47.75	-97.17	-90.65	-1.65	1.34	3.97	30.17
$WML_{t-6,t-2}$	0.62	2.47	7.25	0.30	-2.60	21.33	-99.21	-66.89	-2.14	1.16	4.19	27.82

Table A4. Correlation of WML, WML_{LL}, WML_{SL}, $rHTP$, and $rPTH$ Excluding the Ten Most Extreme Momentum Crash Months

This table displays the return correlation coefficients for monthly WML, long leg-based WML, short leg-based WML, $rHTP$, and $rPTH$. For each month t, WML is the value-weighted return difference between top- and bottom-MOM decile. WML_{LL} is the value-weighted return difference between top-MOM decile and medium-MOM deciles (average return of deciles two to nine). WML_{SL} is the value-weighted return difference between medium-MOM deciles (average return of deciles two to nine) and bottom-MOM decile. $rHTP$ ($rPTH$) is the value-weighted return difference between top-HTP (PTH) decile and bottom-HTP (PTH) decile portfolios. Stocks are allocated to these decile portfolios at the end of each month $t-1$ using NYSE-breakpoints. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The t-statistics for correlation coefficients are shown in the right part of the table. The sample period covers January 1927 to December 2018. We exclude the ten most extreme momentum crash months considered in Table 2 here.

	Correlation Coefficient					t-statistics				
	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$
WML	1.00									
WML_{LL}	0.71	1.00				33.12				
WML_{SL}	0.81	0.16	1.00			45.25	5.19			
$rHTP$	0.46	0.76	0.00	1.00		16.89	38.56	0.08		
$rPTH$	0.68	0.15	0.83	-0.16	1.00	30.59	4.94	48.56	-5.30	

Table A5. *MOM*, *HTP*, and *PTH* in Value-Weighted Fama-MacBeth-Regressions
This table reports time-series averages of monthly estimates from value-weighted cross-sectional regressions. The dependent variable is the stock return of month t. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. $BETA$ is the market beta defined as in Hou et al. (2020) based on daily returns of month $t-1$ including one market lead and lag return. $SIZE$ is the log market capitalization at the end of month $t-1$ and BM the book-to-market ratio based on the firms's market capitalization at the end of month $t-1$ and the book equity which is updated at the end of each June based on annual accounting data from the preceding calendar year following Fama and French (1993). $ILLIQ$ denotes stock illiquidity following Amihud (2002), REV the stock return in month $t-1$, $IVOL$ the annualized idiosyncratic return volatility of daily returns in month $t-1$ relative to the three-factor model of Fama and French (1993) as introduced by Ang et al. (2006), and $IMOM$ the log intermediate momentum return from months $t-12$ to $t-7$ as in Novy-Marx (2012). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers January 1927 to December 2018.

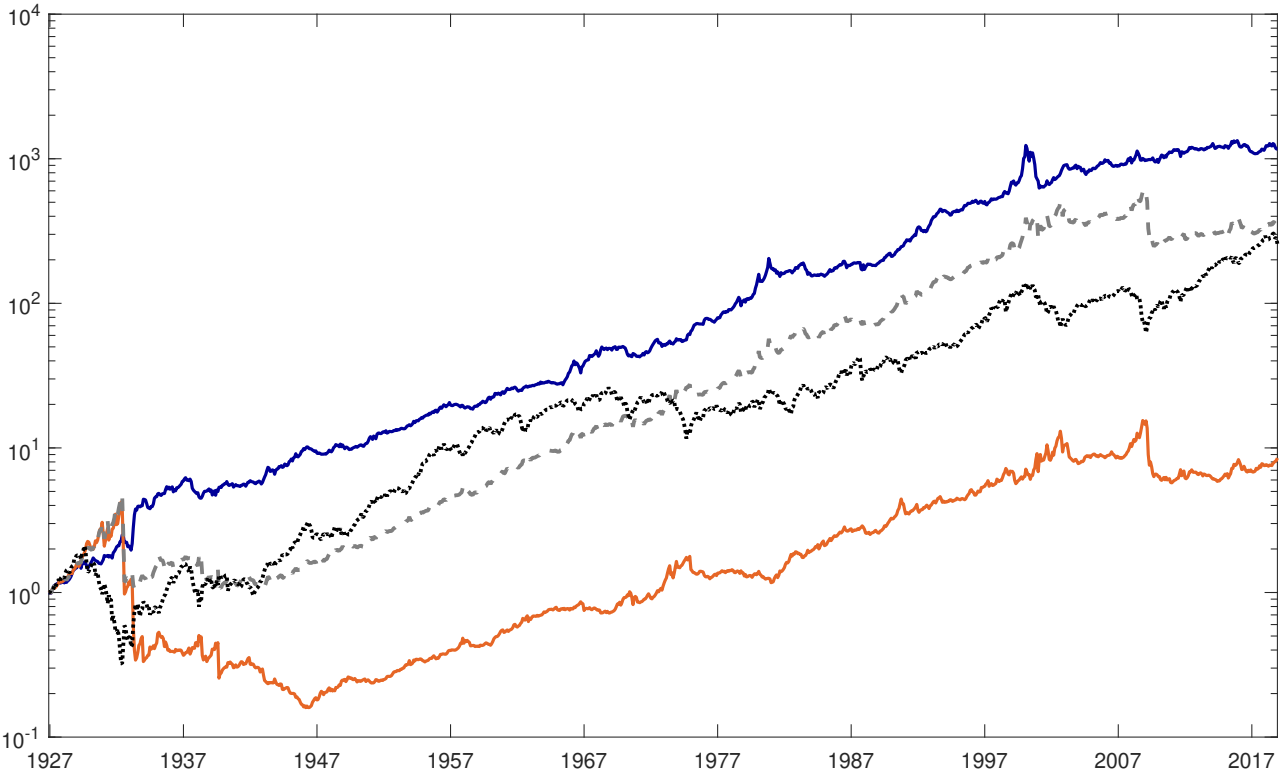
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
intercept	0.65	0.52	0.97	0.59	1.23	2.16	2.27
	(4.33)	(3.33)	(6.51)	(4.27)	(2.64)	(4.35)	(4.72)
MOM	1.31						
	(6.89)						
HTP		1.72		1.66	1.62	1.85	1.65
		(6.66)		(6.34)	(7.00)	(7.90)	(5.10)
PTH			1.21	1.23	1.42	1.06	1.06
			(2.99)	(3.20)	(4.44)	(3.40)	(3.32)
BETA					-0.05	-0.02	-0.02
					(-1.27)	(-0.53)	(-0.43)
SIZE					-0.03	-0.06	-0.07
					(-1.60)	(-3.21)	(-3.51)
BM					0.15	0.13	0.12
					(3.10)	(2.47)	(2.44)
ILLIQ						0.01	0.01
						(1.95)	(1.82)
REV						-0.03	-0.03
						(-6.75)	(-7.06)
IVOL						-1.43	-1.39
						(-5.83)	(-5.93)
IMOM							0.27
							(0.82)

Table A6. Monthly Long-Short Returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$
This table displays summary statistics for monthly WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 2018.

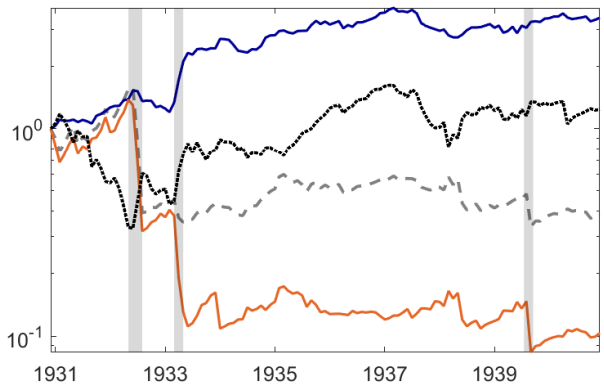
	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML^{FF}	0.66	4.83	4.74	0.49	-3.22	33.41	-78.77	-53.99	-0.95	0.81	2.88	18.24
$rHTP^{FF}$	0.70	5.99	3.37	0.72	0.87	11.77	-49.35	-17.43	-0.97	0.62	2.41	28.31
$rPTH^{FF}$	0.37	2.17	5.49	0.24	-3.39	30.06	-96.21	-53.19	-1.24	0.81	2.58	20.39

Figure A2. Cumulative Long-Short Returns
This figure shows the cumulative monthly long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. In addition, this figure shows the cumulative excess market return MKT.

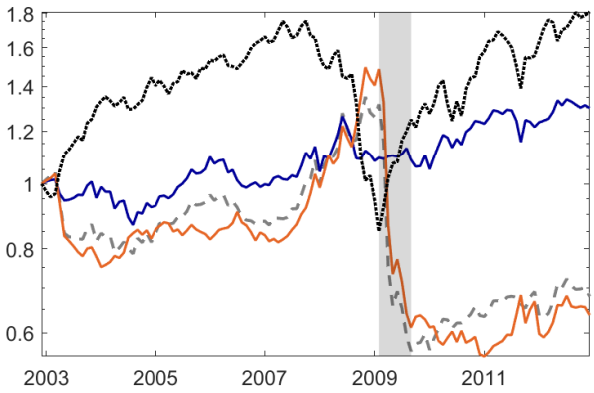
Panel A: January 1927 to December 2018



Panel B: January 1931 to December 1940



Panel C: January 2003 to December 2012



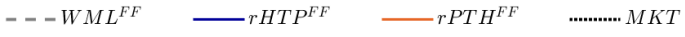


Table A7. Most Extreme Momentum Crash Months
This table shows WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ for those ten months t in the sample period that show the most negative return WML^{FF}. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. In addition, the table shows the market excess return of month t (MKT) as well as the cumulative market excess return of months $t-24$ to $t-1$ (MKT_{24m}). The sample period covers January 1927 to December 2018.

month	WML^{FF}	$rHTP^{FF}$	$rPTH^{FF}$	MKT	MKT_{24m}
1932-08	-53.99	-10.42	-53.19	37.06	-68.46
1932-07	-46.22	-0.86	-47.59	33.84	-75.47
2009-04	-34.98	0.88	-34.52	10.19	-43.51
1939-09	-30.34	6.89	-43.16	16.88	-21.62
2001-01	-25.32	-3.27	-25.01	3.13	-0.28
1938-06	-23.66	3.07	-25.56	23.87	-28.23
1931-06	-18.38	-2.58	-17.25	13.90	-50.52
1933-04	-17.33	28.31	-49.56	38.85	-59.65
2002-11	-16.33	3.97	-19.42	5.96	-40.12
1975-01	-13.64	5.77	-19.02	13.66	-49.71

Table A8. Subperiod Analyses of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$

This table shows average monthly returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ for different market state and return dispersion subperiods. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. Following Cooper et al. (2004), the up (down) market state subperiod includes all months t for which the market return over months $t-36$ to $t-1$ is positive (negative). Following Stivers and Sun (2010), for each month, return dispersion is measured as the cross-sectional return standard deviation of 100 size/book-to-market portfolios (obtained from Kenneth R. French's homepage). Each month t is considered as high (low) return dispersion month if the average return dispersion of months $t-3$ to $t-1$ is above (below) the time-series median. The t-statistics in parentheses refer to the subperiod average returns of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ and are based on standard errors following Newey and West (1987) using twelve lags. Δ refers to the difference between the two respective subperiods. The corresponding t-statistics are based on two-sample t-tests (Welch's t-test with unequal variances). The sample period covers January 1927 to December 2018.

	WML^{FF}				$rHTP^{FF}$				$rPTH^{FF}$			
	MktState		RetDisp		MktState		RetDisp		MktState		RetDisp	
	Up	Down	Low	High	Up	Down	Low	High	Up	Down	Low	High
mean	0.83	-0.43	0.97	0.36	0.60	1.06	0.62	0.78	0.61	-1.17	0.87	-0.13
t	(7.16)	(-0.65)	(7.78)	(1.36)	(5.17)	(2.68)	(5.29)	(3.87)	(5.12)	(-1.36)	(6.93)	(-0.39)
Δ	1.26		0.61		-0.46		-0.16		1.78		1.00	
t	(2.10)		(2.14)		(-1.15)		(-0.70)		(2.33)		(2.98)	

Figure A3. Winner and Loser Stocks in Long and Short Leg of *HTP*- and *PTH*-Strategies
The two bars on the left show the time-series average proportion of winner stocks assigned to different HTP-portfolios (PTH-portfolios). The two bars on the right show the time-series average proportion of loser stocks assigned to different HTP-portfolios (PTH-portfolios). Winner and loser stocks as well as low, medium, and high HTP-portfolios (PTH-portfolios) are defined in accordance with the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. The bars show the proportion of winner and loser stocks that are simultaneously identified as low-, medium-, or high-HTP (PTH). MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The sample period covers January 1927 to December 2018.

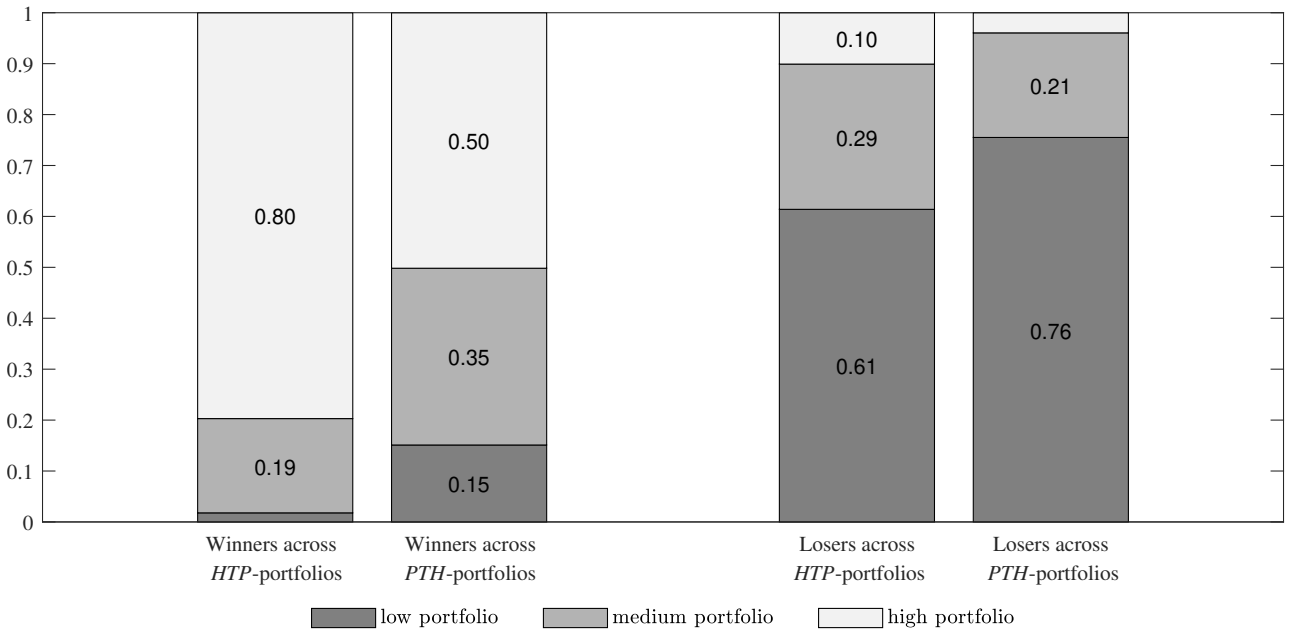


Table A9. Correlation of WML^{FF}, WML^{FF}_{LL}, WML^{FF}_{SL}, $rHTP^{FF}$, and $rPTH^{FF}$
This table displays the return correlation coefficients for monthly WML^{FF}, long leg-based WML^{FF}, short leg-based WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$. WML^{FF} is the long-short return based on MOM defined in accordance with Fama and French (2018). WML^{FF}_{LL} is the return difference between the top 30% and medium 40% MOM-portfolios. WML^{FF}_{SL} is the return difference between medium 40% and bottom 30% MOM-portfolios. $rHTP^{FF}$ and $rPTH^{FF}$ are the long-short returns based on HTP and PTH, respectively, defined in accordance with the methodology of Fama and French (2018). MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The t-statistics for each correlation coefficient are shown in the right part of the table. The sample period covers January 1927 to December 2018.

	Correlation Coefficient					t-statistics				
	WML^{FF}	WML^{FF}_{LL}	WML^{FF}_{SL}	$rHTP^{FF}$	$rPTH^{FF}$	WML^{FF}	WML^{FF}_{LL}	WML^{FF}_{SL}	$rHTP^{FF}$	$rPTH^{FF}$
WML^{FF}	1.00									
WML^{FF}_{LL}	0.83	1.00				50.17				
WML^{FF}_{SL}	0.88	0.47	1.00			61.62	17.80			
$rHTP^{FF}$	0.41	0.61	0.13	1.00		15.04	25.64	4.48		
$rPTH^{FF}$	0.78	0.47	0.85	-0.15	1.00	41.45	17.49	52.67	-5.14	

Figure A4. Loser Stocks in Short Leg of *HTP*- and *PTH*-Strategies
This figure shows the proportion of loser stocks assigned to the low-HTP (low-PTH) portfolios. These bottom portfolios are identified in accordance with the UMD momentum factor construction by Fama and French (2018). The graphs show the proportion of loser stocks that are simultaneously identified as low-HTP (low-PTH) stocks. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.

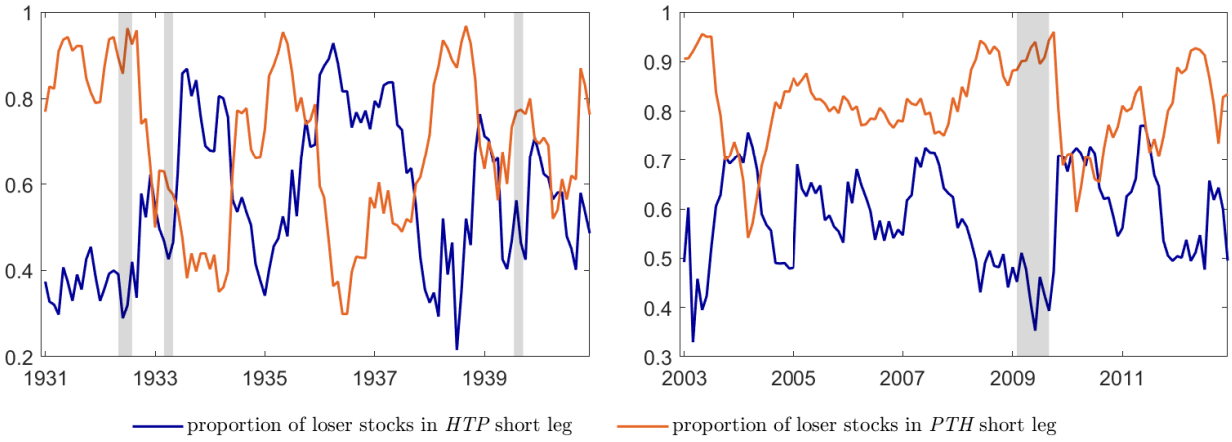


Table A10. Time Varying Market Betas and Optionality of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$
This table shows regression coefficients for the time-series regression $WML_t^{FF} = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t$. In alternative specifications, $rHTP^{FF}$ and $rPTH^{FF}$ are used as dependent variables instead of WML^{FF}. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. MKT_t is the excess market return in month t. B_t is a bear market dummy which equals one if the excess market return over months $t-24$ to $t-1$ is negative and zero otherwise. R_t is a rebound dummy which equals one if the excess market return in month t is positive and zero otherwise. 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 sample period covers January 1927 to December 2018.

	WML^{FF}			$rHTP^{FF}$			$rPTH^{FF}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
α_0	0.86	0.87	0.87	0.53	0.39	0.39	0.81	0.91	0.91
t	(7.55)	(7.98)	(7.98)	(4.70)	(3.51)	(3.51)	(6.80)	(8.53)	(8.52)
α_B		-1.07	0.62		0.53	-0.07		-1.55	0.91
t		(-2.40)	(0.85)		(1.59)	(-0.10)		(-3.01)	(1.76)
β_0	-0.30	0.03	0.03	0.27	0.36	0.36	-0.67	-0.41	-0.41
t	(-2.78)	(0.68)	(0.68)	(4.59)	(8.99)	(8.99)	(-7.55)	(-8.96)	(-8.96)
β_B		-0.73	-0.42		-0.20	-0.31		-0.56	-0.11
t		(-5.69)	(-4.38)		(-1.83)	(-4.13)		(-5.73)	(-1.46)
$\beta_{B,R}$			-0.53			0.19			-0.77
t			(-2.09)			(0.82)			(-6.43)

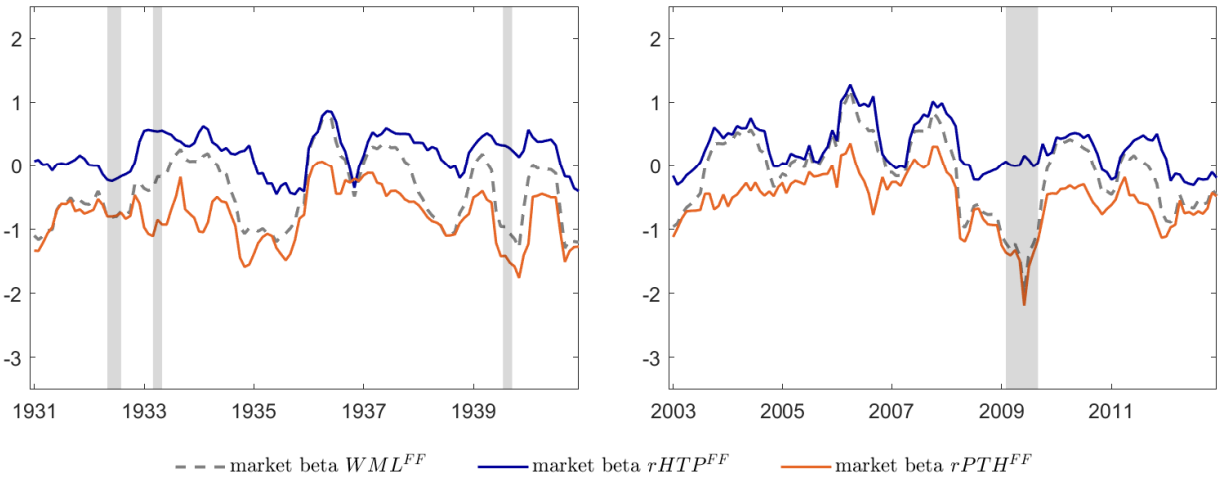



Figure A5. Rolling Market Betas of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$
This figure shows rolling market betas for daily factor returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on MOM, HTP, or PTH and two size portfolios. Each month, the MOM, HTP, and PTH breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. WML^{FF} ($rHTP^{FF}$, $rPTH^{FF}$) is defined as the mean return of the two high-MOM (HTP, PTH) portfolios minus the mean return of the two low-MOM (HTP, PTH) portfolios. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM which is realized before the formation period's highest stock price P_{high}. PTH refers to the return component of MOM which is realized after the formation period's highest stock price P_{high}. Market betas are based on six-month rolling windows of daily returns and take into account ten daily lags for the market return. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.