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 as the momentum crashes are driven by the second component's short leg dependence on recent loser stocks. The crash-resilient strategy allows for significant momentum profits even in recent years, avoids the latest Covid-19 momentum crash, and is valid in both the US and international stock markets.

Keywords: Momentum, Momentum crashes, 52-Week high, Cross-section of stock returns

JEL: G11, G12

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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 US momentum stocks and short in the lowest decile has yielded an average monthly return of 1.18% over the period from 1927 to 2020. Simultaneously, 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 has been -77.56%. The momentum strategy 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 the form of crashes when the market rises. For example, such momentum crashes can be observed during the Great Depression in the 1930s, after the financial crisis in 2009, and following the recent Covid-19 induced stock market downturn in 2020.

In this study, we show that a simple decomposition of momentum allows for such crashes to be avoided. More specifically, we decompose momentum's formation period return, MOM, into the two components high-to-price (HTP) and price-to-high (PTH) 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, that is, 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 is the log ratio of this high price to the initial stock price such that it can be expressed as the difference between MOM (log momentum return) and PTH (log ratio of final stock price to high price):

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

where P_0 and P_1 denote the stock prices at the beginning ($t-12$) and end ($t-2$), respectively, of the momentum formation period. Prior research has extensively documented the positive cross-sectional relationship between MOM and subsequent returns in month t. Moreover, PTH – conceptually similar to the 52-week high measure provided by George and Hwang (2004) – has been shown to predict subsequent returns and 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 higher 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 0.48% per month and a Sharpe ratio of 0.19 in the cross-section of US stock returns. 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. 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, loser stocks experience sharp increases in their prices, leading to negative market risk exposure and crashes of the PTH-strategy. After removing this crash-prone PTH-component from momentum, the remaining HTP-component yields a monthly return premium of 1.21% and a Sharpe ratio of 0.72 – thereby outperforming the traditional momentum strategy (Sharpe ratio of 0.52). 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. Upon investigating the underlying economic mechanism, we find that the HTP-strategy's short leg largely avoids recent loser stocks; consequently, it neither shows a negative market risk exposure nor crashes when these loser stocks recover after severe market drawdowns.

Given that the HTP-strategy avoids the momentum crashes following the 2009 financial crisis and the Covid-19 pandemic, it yields significant return premiums even in the most recent quarter of our sample period. For the MOM- and PTH-strategies, this is not the case. Further, we find that the stocks underlying the HTP-strategy are traded with even slightly higher liquidity than standard momentum. Hence, potential transaction costs are similar in magnitude and do not wipe out HTP-induced return premiums. Beyond this US evidence, our international analyses show that the HTP-strategy also yields crash-resilient positive return premiums in continental Europe, Asia, America (excluding the US), and the UK. HTP even induces significant return premiums in Japan, whereas classical momentum does not.

Beyond separately investigating the PTH- and HTP-strategies, 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 (long) leg. Third, after market downturns, momentum is largely determined by its PTH-component such that it crashes similarly to the PTH-strategy and cannot profit from the crash-resilient nature of HTP.

We extend the existing literature in five directions. First, we add to the extensive debate on momentum crashes and their sources (Chabot et al., 2014; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Daniel et al., 2019; Luo et al., 2021; Barroso et al., 2021). 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 using constant-target-volatility and dynamic strategies, respectively. They show that the volatility of momentum strategy returns predicts momentum crashes. Consequently, their strategies allow to avoid severe momentum crashes by systematically reducing the investment exposure during high-volatility periods.[1] We show that a simple static cross-sectional strategy based on HTP can also avoid these crashes, but without time-series adjustments of investment exposure – that is, we propose a new, simple method to reduce the risk of momentum investing.

Second, higher average returns and Sharpe ratios of the HTP-based momentum strategy might provide an increased challenge to existing theories that aim at explaining the overall momentum phenomenon (e.g., Daniel et al., 1998; Hong and Stein, 1999; Grinblatt and Han, 2005; Antoniou et al., 2013; and Asness et al., 2013). For example, our findings indicate that the economic drivers of momentum profits are not identical to the drivers of momentum crashes (Guo et al., 2021). In particular, momentum profits are not merely a compensation for momentum crash risk as we can hedge out these crashes without sacrificing cross-sectional return predictability. In a similar vein, we show that several established asset

[1] Similarly, Huang (2021) shows that the momentum gap, the formation period return difference between winner and loser stocks, allows to predict and avoid momentum crashes. Furthermore, Han et al. (2016) propose a stop-loss strategy, and Dierkes and Krupski (2022) combine the insights of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) to circumvent momentum crashes. While these strategies adjust the investment exposure across time to alleviate momentum crashes, other approaches restrict the cross-sectional strategy to specific stocks. For example, Chuang and Ho (2014), Yang and Zhang (2019), and Hoberg et al. (2022) exclude stocks based on their price risk, extreme absolute strength, and buy-side competition, respectively. By contrast, our strategy based on HTP uses the full cross-section of stocks.

pricing factor models capture the return premiums associated with MOM and PTH, but not the HTP-induced premiums.

Third, we contribute 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. Similarly, the profitability of both MOM- and PTH-strategies strongly depends on market conditions as their average returns are only positive in up market states (Cooper et al., 2004; Barroso and Wang, 2021) and in times of low cross-sectional return dispersion (Stivers and Sun, 2010). We show that this observation does not apply to 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 conditions and thereby questions explanatory approaches to momentum that rely on its market state dependence (Guo et al., 2021).

Fourth, 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 (e.g., Huddart et al., 2009; Driessen et al., 2012; Bhootra and Hur, 2013; Lee and Piqueira, 2017; George et al., 2017, 2018; and Zhu, 2020). Related to momentum crashes, parallel research by Byun and Jeon (2018) and Barroso and Wang (2021) shows that long-short strategies based on this 52-week high distance are prone to severe crash risk, too. However, all these papers focus on a stock's return after the 52-week high while we examine its return before the high price. 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 generate substantially higher returns and Sharpe ratios than the extensively examined PTH-based strategies.

Fifth, our analyses are related to research examining the return predictability of momentum subperiods. In this context, Novy-Marx (2012) shows that momentum profits in month t are driven by formation months $t-12$ to $t-7$ (intermediate momentum) rather than formation months $t-6$ to $t-2$. As HTP covers the beginning of the overall momentum formation period, it is by construction related to intermediate momentum. However, our analyses show that the flexible formation period split via the high price is essential for eliminating momentum crashes as the intermediate momentum strategy of Novy-Marx (2012) crashes even more severely than traditional momentum. Moreover, in cross-sectional regression analyses, HTP captures the return predictability associated with intermediate momentum, but not vice versa.

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. The underlying drivers of the long-short strategies' different crash risks are examined in Section 4. In Sections 5 and 6, we provide further time-series and cross-sectional evidence on the documented return predictability, respectively. Finally, we present the international stock market evidence in Section 7 and conclude in Section 8.

2. Data and Variables

Our US stock market analyses are mainly based on return data obtained from the Center for Research in Security Prices (CRSP). Data on the excess market return MKT beginning in July 1926 is obtained from Kenneth R. French's homepage.[2] Book equity data is retrieved from COMPUSTAT and, for the beginning of our sample period, from Kenneth R. French's homepage. 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.[3]

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, that is, 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

[2] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.
[3] CRSP and COMPUSTAT data were provided by Wharton Research Data Services.

based on NYSE-breakpoints. The long-short returns of month t are defined as the difference between the value-weighted returns of the top and bottom decile portfolio.[4] We account for delisting returns following the procedure proposed by Shumway (1997).[5]

Our US 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 2020 since CRSP data go back to 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 the main variables of interest MOM, HTP, and PTH can be calculated, that is, if stock return data for the previous twelve months are available. This leads to a total of 3,243,989 stock-month-observations.

3. Evidence on Momentum Crashes

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 $rPTH$.[6] We document a significant momentum effect of 1.18% per month. Both HTP and PTH yield positive return spreads, too, i.e., both momentum components contribute to the overall momentum phenomenon. While the 1.21% average return spread associated with HTP is highly significant, the PTH-induced return premium of 0.48% is associated with a t-statistic of

[4] As a robustness test, we also conduct all of our analyses with long-short returns that are constructed according to the UMD momentum factor construction 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 the Online Appendix.

[5] 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`.

[6] Average returns for each of the ten decile portfolios are provided in the Online Appendix.

only 1.82. Hence, 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 although it has not received any research attention so far.

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.18	5.45	7.87	0.52	-2.26	19.36	-95.35	-77.56	-1.74	1.54	5.06	25.83
$rHTP$	1.21	6.59	5.77	0.72	0.08	8.33	-66.91	-32.80	-1.66	0.92	4.27	35.36
$rPTH$	0.48	1.82	8.85	0.19	-2.63	21.82	-99.88	-83.40	-2.36	1.34	4.29	33.34

Turning to the volatility of the long-short strategies, $rPTH$ shows the highest standard deviation resulting in a comparably low Sharpe ratio of 0.19. For $rHTP$, the low standard deviation contributes to its high Sharpe ratio of 0.72 – clearly exceeding the momentum Sharpe ratio of 0.52. Moreover, in contrast to $rHTP$, the long-short returns WML and $rPTH$ are negatively skewed and much more leptokurtic. This observation provides initial evidence that both the MOM- and the PTH-strategy induce higher tail and crash risk than the HTP-strategy. To further delineate this, we 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 monthly investment strategy. While we confirm previous literature on severe momentum crashes (maximum WML drawdown of -95.35%), 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 -66.91% 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. Simultaneously, upon removing PTH from MOM, the resulting HTP-strategy yields long-short returns with slightly positive skewness and substantially reduced crash risk.

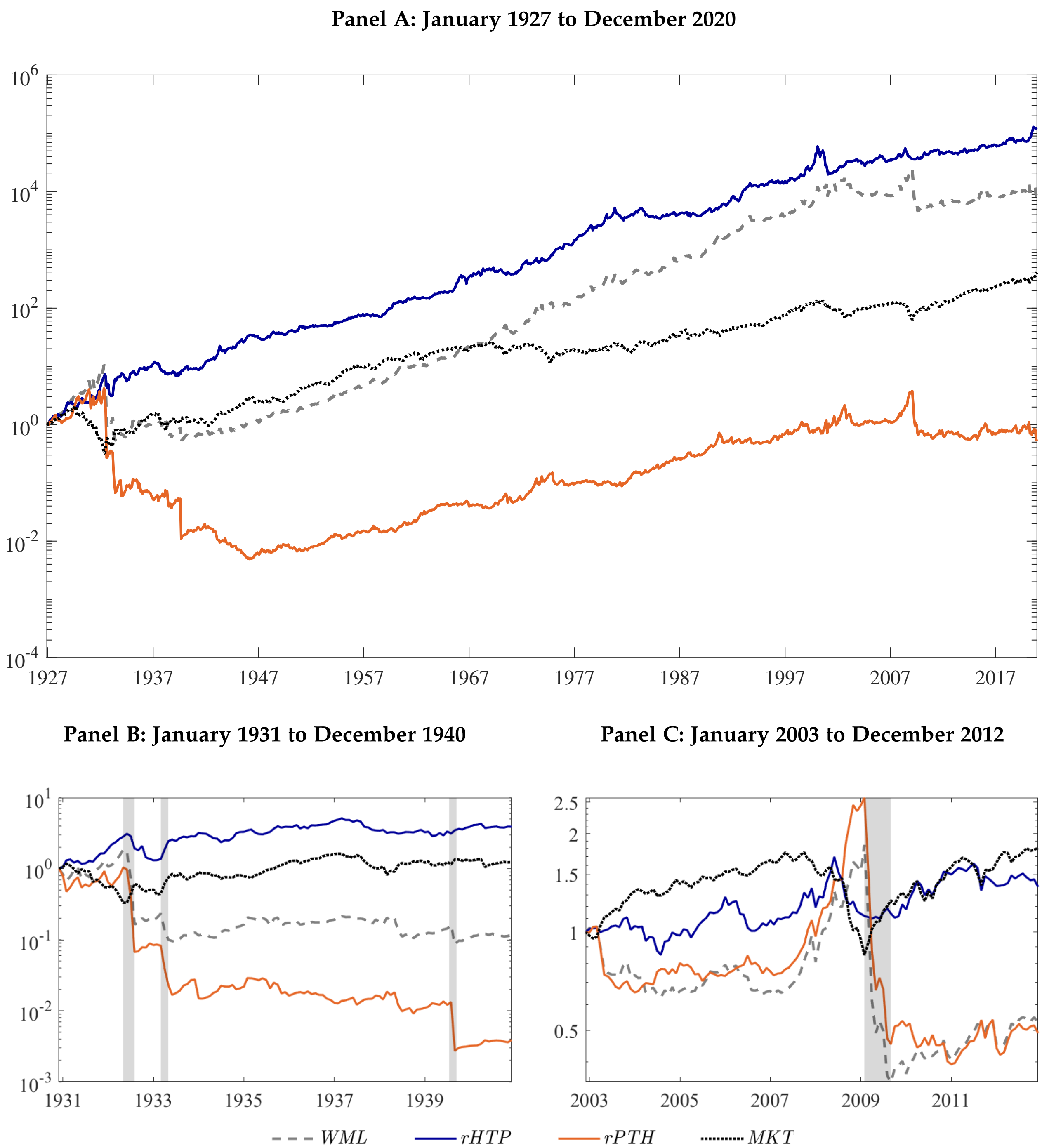
To visualize the summary statistics from Table 1, Figure 1 depicts the cumulative returns of WML, $rHTP$, $rPTH$, and the excess market return MKT for the entire sample period in Panel A. From 1927 to 2020, $rHTP$ yields the highest cumulative return and outperforms the standard winner-minus-loser strategy WML. More specifically, a hypothetical \$1 investment in $rHTP$ in January 1927 resulted in \$117,202.00 at the end of 2020 while a corresponding WML-strategy resulted in only \$8,457.54. At first sight, it might be surprising that the cumulative return of the HTP-strategy is that much higher than that of the WML-strategy even though their mean monthly returns are similar (see Table 1). This is because $rHTP$ does not crash severely such that its geometric mean is substantially higher than WML's. 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 in $rPTH$ in 1927 results in only \$0.52 at the end of 2020. Naturally, this does not imply a weak $rPTH$-performance during all subperiods: for example, the George and Hwang (2004) sample period from July 1963 to December 2001 does not include severe crashes. Hence, a \$1 investment grows to \$30.67 in this sample period supporting the strong seminal findings on the return predictability of the 52-week high.

Figure 1 further indicates that WML does not yield substantial return premiums during the last quarter of our sample period (July 1997 to December 2020). This observation is mainly due to the recent momentum crashes in 2009 and 2020 and is in line with Bhattacharya et al. (2012) and Yang and Zhang (2019) who also document a recently deteriorating profitability of momentum strategies. We provide more detailed subperiod evidence in the Online Appendix: the average monthly long-short returns WML and $rPTH$ are indeed insignificant from July 1997 to December 2020. In contrast, $rHTP$ yields a significant monthly return premium of 0.92% during this period. Hence, by dropping the PTH-component from MOM, the HTP-strategy avoids the 2009 and 2020 momentum crashes and allows for significant momentum profits even in recent years. Moreover, the Online Appendix shows that $rHTP$ is significantly positive in each quarter of our sample period while MOM and $rPTH$ yield significant return premiums in only two out of the four subperiods.[7]

In the following, we 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 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 greater detail. The two subplots demonstrate that WML

[7] Figure 1 shows a strong detrimental impact of the 1930s on WML and $rPTH$. Note, however, that our main findings in Table 1 are not merely driven by this decade: an analysis of monthly long-short returns based on the frequently applied more recent sample period beginning in July 1963 (George and Hwang, 2004) reveals very similar summary statistics (see Online Appendix).

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. In addition, this figure shows the cumulative excess market return MKT.



and $rPTH$ crash simultaneously, whereas $rPTH$ crashes even more severely than WML.[8] Moreover, these crashes tend to occur after market downturns when the market rebounds. Conversely, $rHTP$ shows rather smooth progress over time with 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 than 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 constant volatility, i.e, their strategy reduces WML exposure in times of high volatility when crashes are more likely (also see similar approaches in Han et al., 2016, Moreira and Muir, 2017, Huang, 2021, and Dierkes and Krupski, 2022). 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. 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. (2022) eliminate specific subgroups of stocks from the construction of momentum portfolios to reduce crash risk. In contrast, 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 completely avoids negative return skewness. Hence, crashes are no inherent property of momentum strategies but can be avoided by simply eliminating PTH from momentum's formation period. This observation also shows that average momentum returns cannot be completely

[8]We highlight the momentum crashes by gray bars in Panels B and C for illustrative reasons and also show these bars in the following graphs for easier orientation.

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 the monthly long-short portfolio returns WML, $rHTP$, and $rPTH$ for the ten months t in the sample period with 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. In addition, the table shows the market excess return of month t (MKT) and the cumulative market excess return of months $t-24$ to $t-1$ (MKT_{24m}). The sample period covers January 1927 to December 2020.

month	WML	$rHTP$	$rPTH$	MKT	MKT_{24m}
Aug 1932	-77.56	-32.80	-83.40	37.06	-68.46
Jul 1932	-58.25	-7.15	-58.53	33.84	-75.47
Sep 1939	-45.93	11.27	-79.48	16.88	-21.62
Apr 2009	-45.10	-1.14	-44.22	10.18	-43.51
Jan 2001	-41.81	-14.34	-39.56	3.13	-0.28
Apr 1933	-41.21	35.36	-51.91	38.85	-59.65
Mar 2009	-39.21	-0.81	-39.01	8.95	-47.79
Jun 1938	-32.49	-4.55	-33.15	23.87	-28.23
Jun 1931	-29.44	-9.24	-28.16	13.90	-50.52
Apr 2020	-29.20	-0.68	-36.16	13.65	-4.76

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}). Eight out of the ten months were part of the Great Depression in the 1930s or the financial market crisis in 2009. The only exceptions are January 2001 with a WML-return of -41.81% following the stock market downturn after the turn of the millennium and April 2020 with a WML-return of -29.20% following the outbreak of the Covid-19 pandemic. Notably, for each of the ten crash months, $rHTP$ yields higher returns than WML while $rPTH$ crashes to a similar extent as WML. These observations 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.

An additional 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 $rPTH$ but not to $rHTP$. We will investigate the underlying mechanisms for this different behavior in the following section.

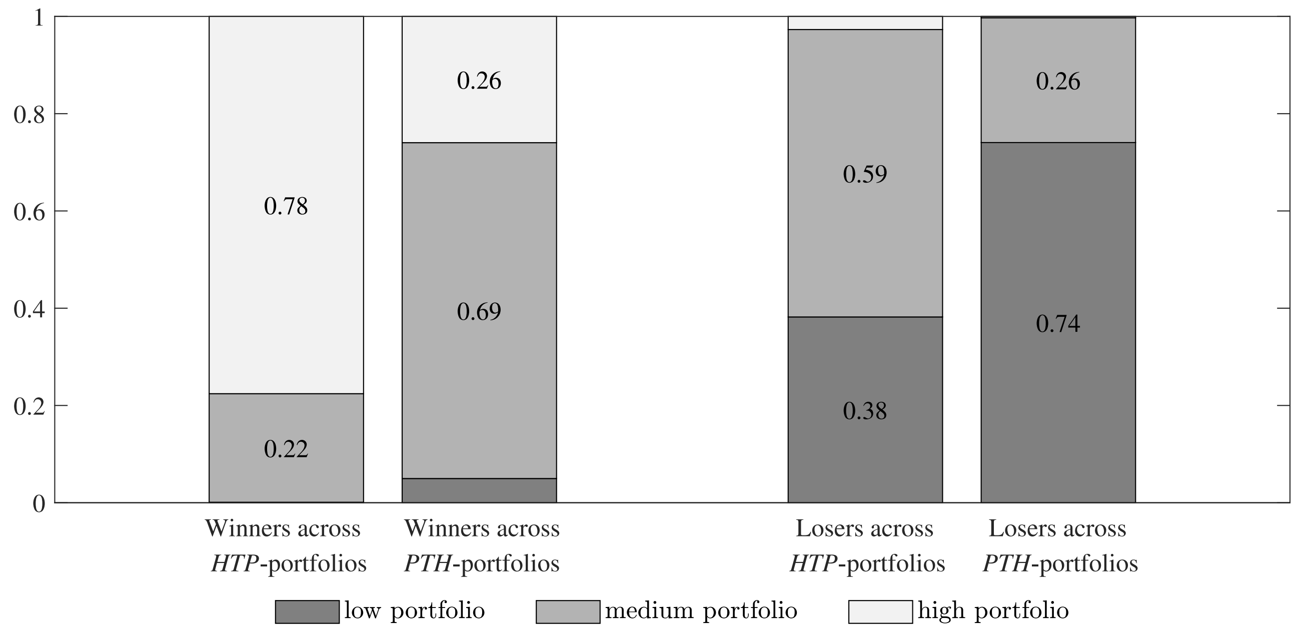
4. Drivers of Momentum Crashes

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, recall that 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 than 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. Therefore, we examine to what extent winner and loser stocks also show up in the extreme HTP- and PTH-deciles. Figure 2 shows the locations of winner and loser stocks across the top-, bottom-, and medium-HTP (PTH) decile portfolios, that is, it shows whether the winners and losers show up in the HTP (PTH) strategy's long leg, short leg, or neither 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, that is, 78% of stocks in the top-MOM decile are also part of the top-HTP decile. In contrast, only 26% of winner stocks 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 for why $rPTH$ crashes more severely than $rHTP$.

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The sample period covers January 1927 to December 2020.



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 3. It presents correlation coefficients for WML, long and 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 (winners) and the mean of the 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 (losers). This methodology implies that WML is split up into its long and short leg component such that $WML = WML_{LL} + WML_{SL}$.

Table 3. 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 the 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The t-statistics for the correlation coefficients are shown in the right part of the table. The sample period covers January 1927 to December 2020.

	Correlation Coefficient					t-statistics				
	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$
WML	1.00									
WML_{LL}	0.75	1.00				37.95				
WML_{SL}	0.86	0.31	1.00			57.22	10.98			
$rHTP$	0.38	0.69	0.02	1.00		13.91	31.76	0.83		
$rPTH$	0.79	0.34	0.87	-0.10	1.00	43.18	12.18	59.86	-3.29	

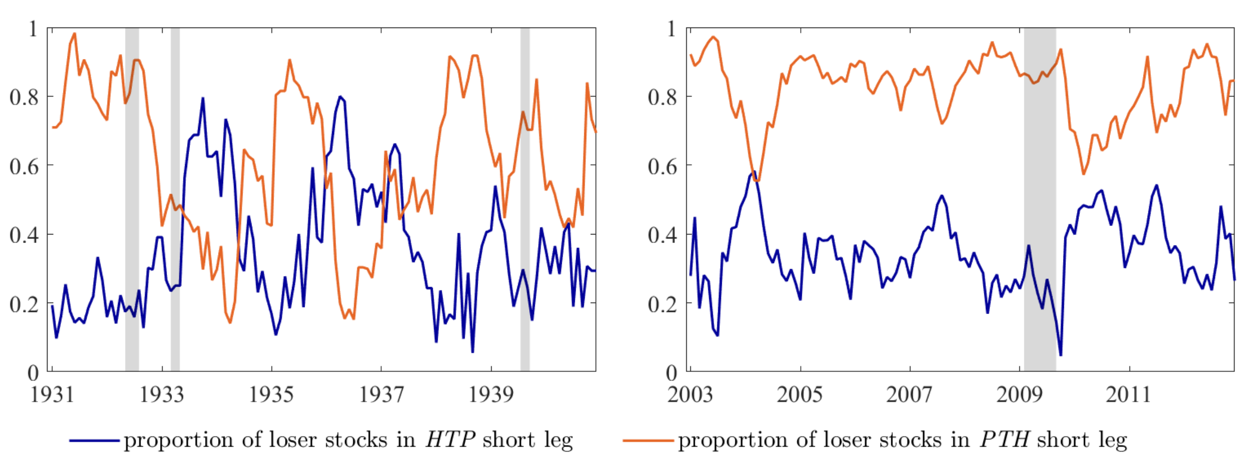
As expected, both $rHTP$ and $rPTH$ show a significantly positive correlation with WML as the underlying variables HTP, PTH, and MOM are linearly related by construction. Notably, the correlation between $rPTH$ and WML is considerably higher than that of $rHTP$ and WML. This is consistent with the graphical evidence in Figure 1, which illustrates that WML and $rPTH$ crash simultaneously.[9] Further, the correlation between WML_{LL} and $rHTP$ is 69%, while that of WML_{LL} and $rPTH$ is only 34%. This observation aligns with the evidence from Figure 2 that winner stocks (which contribute to WML_{LL}) influence the HTP- rather than 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,

[9] 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 1,128-month sample, the WML-$rPTH$-correlation already drops to 0.70 while the WML-$rHTP$-correlation increases to 0.42 (see Online Appendix).

Table 3 provides clear-cut 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 the loser stocks in the momentum strategy's short leg.

The different prevalence of loser stocks in the PTH versus HTP strategy's short leg (see Figure 2) 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 with 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) over 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 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 gray 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. Thus, 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 those firms' values. 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 the extent to which differences in these optionality characteristics can explain why $rPTH$ crashes while $rHTP$ does not. To do so, Table 4 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 4 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 0.34 ($t = 3.37$) while the long-short strategy based on PTH has a negative market beta of -1.03 ($t = -9.54$). 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. Conversely, 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 1.83% ($t = -2.71$) and 2.47% ($t = -2.98$), respectively, and thus turn negative. 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 -1.42).

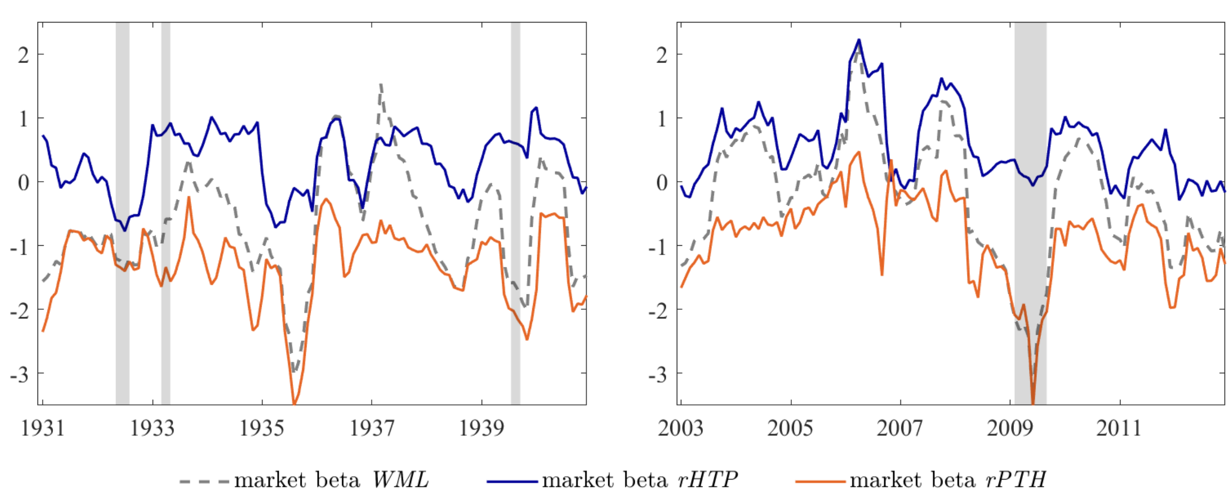
Table 4. Time Varying Market Betas and Optionality of WML, $rHTP$, and $rPTH$
This table shows regression coefficients for the time-series regression $WML_t = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t$. In alternative specifications, $rHTP$ and $rPTH$ 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 July 1928 to December 2020 as we need 24 months of market returns to define the bear market dummy.

	WML			$rHTP$			$rPTH$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
α_0	1.52	1.62	1.62	0.96	0.78	0.78	1.15	1.41	1.41
t	(8.60)	(8.85)	(8.84)	(4.94)	(4.21)	(4.21)	(6.10)	(7.91)	(7.91)
α_B		-1.83	0.59		0.64	0.38		-2.47	0.53
t		(-2.71)	(0.66)		(1.13)	(0.32)		(-2.98)	(0.65)
β_0	-0.55	-0.06	-0.06	0.34	0.53	0.53	-1.03	-0.68	-0.68
t	(-3.69)	(-0.80)	(-0.80)	(3.37)	(8.43)	(8.42)	(-9.54)	(-9.79)	(-9.78)
β_B		-1.07	-0.63		-0.41	-0.45		-0.74	-0.20
t		(-6.83)	(-4.50)		(-2.25)	(-3.48)		(-5.53)	(-1.61)
$\beta_{B,R}$			-0.75			0.08			-0.93
t			(-3.29)			(0.22)			(-4.63)

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, that is, 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 -1.81. Hence, the overall negative market risk exposure of $rPTH$ is even more negative during bear markets and market rebounds explaining the severe $rPTH$ crashes. In contrast, the market beta of $rHTP$ remains positive when the market recovers from bear markets. In none of the three regression specifications, does $rHTP$ exhibit a negative market beta, which indicates 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 4 suggest that long-short investment strategies based on MOM and PTH are comparable to shorting a call option on the market since 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. Conversely, 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.

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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.



Supplementing Table 4, Figure 4 depicts time-series fluctuations in the strategies' market risk exposure. More specifically, it depicts the 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 market risk exposure of WML following market downturns. In line with the regression estimates in Table 4, the market beta of $rHTP$ tends to be mostly above zero 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 in further understanding 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. These rebound months have a positive market return by definition, implying 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, the HTP short leg does not behave like an out-of-the-money call option on the market after market downturns. Hence, $rHTP$ has no negative market beta when the market rebounds such that it avoids the typical momentum crashes.

5. Further Time-Series Analyses of WML, $rHTP$, and $rPTH$

Our previous analyses indicate that the crash-resilient nature of $rHTP$ could improve the profitability of momentum strategies and potentially reduce the strategies' market state dependence. Moreover, the elevated Sharpe ratio raises the question of whether $rHTP$ is spanned by common factor models similar to WML. We investigate these issues in the following subsections.

5.1. Market State Dependence

Closely related to momentum crashes is the literature on the market state dependence of momentum profits, which demonstrates that momentum strategies only yield positive returns during expansionary periods and not during recessions (Chordia and Shivakumar, 2002; Cooper et al., 2004; Avramov and Chordia, 2006). Cooper et al. (2004) show that momentum profits only exist if the market return over the preceding three years has been 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 5 shows that $rHTP$ is not significantly affected by the market state and that it is significantly positive following both up and down market states. This is in line with the finding that $rHTP$ does not crash following severe market downturns. In contrast, WML and $rPTH$ show significant market state dependence and yield positive return premiums following up market states only. We therefore conclude that momentum's market state dependence is driven by its PTH-component as $rHTP$ 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.

Beyond the market state, the cross-sectional dispersion in stock returns (RetDisp) is also frequently used as a countercyclical indicator (Loungani et al., 1990; Gomes et al., 2003; Stivers, 2003; Zhang, 2005; and Stivers and Sun, 2010). More specifically, Stivers

Table 5. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 July 1929 to December 2020 for the market state analyses, as we need 36 months of market returns to classify months, and January 1927 to December 2020 for the return dispersion analyses.

	WML				$rHTP$				$rPTH$			
	MktState		RetDisp		MktState		RetDisp		MktState		RetDisp	
	Up	Down	Low	High	Up	Down	Low	High	Up	Down	Low	High
mean	1.43	-0.50	1.73	0.63	1.05	1.70	1.16	1.25	0.87	-1.79	1.29	-0.34
t	(7.96)	(-0.55)	(7.82)	(1.69)	(5.54)	(3.10)	(6.02)	(4.03)	(4.12)	(-1.63)	(6.09)	(-0.75)
Δ	1.93		1.10		-0.65		-0.09		2.65		1.63	
t	(2.09)		(2.53)		(-1.12)		(-0.25)		(2.38)		(3.27)	

and Sun (2010) show that momentum profitability depends negatively 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 5. Cross-sectional return dispersion is estimated following Stivers and Sun (2010), and we split the sample into 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. In contrast, $rHTP$ does not depend on the level of return dispersion: it generates monthly return spreads of more than 1% in both subperiods.[10]

5.2. Factor Spanning Tests

The previous literature has extensively examined the relationship between WML and systematic asset pricing factors (see, for example, Hou et al., 2015; Fama and French, 2016). These insights have been used to judge investors' (risk) factor exposure when exploiting momentum and to investigate the underlying sources of momentum profits. For these reasons, we apply factor spanning tests on WML, $rHTP$, and $rPTH$ using eight different factor model specifications. Table 6 presents the resulting factor-adjusted return premiums.[11]

In line with previous findings, early factor models are unable to capture momentum profits, but the q-factors of Hou et al. (2015), the mispricing factors of Stambaugh and Yuan (2017), and the behavioral factors of Daniel et al. (2020) render WML insignificant. Consistent with Barroso and Wang (2021), the long-short returns associated with PTH are also spanned by some of the most commonly applied factor models. Conversely, $rHTP$ yields significant return premiums after accounting for each of the eight factor models. Naturally, given the positive correlation between $rHTP$ and WML (see Table 3), factor models designed to capture momentum also reduce HTP-induced return premiums to a

[10] Beyond up versus down market state and periods of low versus high return dispersion, we also split the time-series of long-short returns based on their lagged return volatility. Barroso and Santa-Clara (2015) and Barroso and Wang (2021) show that WML yields significantly positive return premiums only if the daily volatility of WML over the previous six months is low. Equivalent to our findings in Table 5, we find that this volatility dependence is shared by $rPTH$ while $rHTP$ generates significantly positive returns irrespective of its lagged volatility (see Online Appendix).

[11] Beyond these regression intercepts, we also present regression betas in the Online Appendix, i.e., the exposure of WML, $rHTP$, and $rPTH$ with respect to each of the several factors. The Online Appendix also provides detailed information on the definition of the factor models.

Table 6. Factor Spanning Tests for WML, $rHTP$, and $rPTH$
This table shows intercepts α from time-series regressions based on monthly data with the long-short returns WML, $rHTP$, and $rPTH$ as dependent variables. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The independent variables are based on the market factor (January 1927 to December 2020), the Fama and French (1993) three-factor model (January 1927 to December 2020), the Fama and French (2015) five-factor model (July 1963 to December 2020), the Fama and French (2018) six-factor model including a momentum factor (July 1963 to December 2020), the Hou et al. (2015) q-factor model (January 1967 to December 2020), the Barillas and Shanken (2018) six-factor model (January 1967 to December 2020), the Stambaugh and Yuan (2017) mispricing-factor model (January 1963 to December 2016), and the Daniel et al. (2020) behavioral factor model (July 1972 to December 2020). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	raw	α_{MKT}	α_{FF3}	α_{FF5}	α_{FF6}	α_q	α_{BS6}	α_{SY}	α_{DHS}
WML	1.18	1.56	1.73	1.39	0.33	0.59	0.37	0.11	0.08
t	(5.45)	(8.81)	(9.57)	(4.18)	(2.99)	(1.62)	(2.92)	(0.47)	(0.26)
$rHTP$	1.21	0.97	1.01	1.16	0.59	0.79	0.63	0.57	0.56
t	(6.59)	(5.04)	(5.72)	(5.00)	(3.73)	(2.81)	(3.55)	(2.83)	(2.80)
$rPTH$	0.48	1.17	1.37	0.96	0.21	0.31	0.19	-0.06	-0.41
t	(1.82)	(6.31)	(8.32)	(3.72)	(1.43)	(1.16)	(1.15)	(-0.27)	(-1.46)

substantial extent.[12] However, our time-series regressions suggest that the crash-resilient $rHTP$ at least constitutes a more severe challenge for established factor models than $rPTH$ and WML. This observation questions whether explanatory approaches for momentum that rely on the systematic factor exposure of WML can explain HTP-induced return premiums.

5.3. Transaction Costs

Momentum strategies and their potential exploitability in the light of transaction costs have received considerable attention in both the investment industry and academia (Korajczyk and Sadka, 2004; Lesmond et al., 2004; Barroso and Santa-Clara, 2015). Given that the HTP-strategy entails neither crash risk nor market state dependence and further that

[12]Note that each of the factor spanning tests in Table 6 refers to the longest possible sample period determined by the respective factor data availability. To allow for more clear-cut comparisons between factor models, the Online Appendix presents the same analyses for a shorter sample period that is identical for all columns.

it yields even higher Sharpe ratios than the traditional momentum strategy, we examine the transaction costs associated with $rHTP$ in the following. To compare the strategies' trading costs, we calculate their average monthly turnover and use end-of-month average half-spreads as a transaction costs proxy. This procedure follows Medhat and Schmeling (2021) who argue that half-spreads represent a conservative cost estimate, as they assume that traders demand immediate liquidity. In line with Barroso and Santa-Clara (2015), the one-way turnover $x_{t,d}$ for decile portfolio d required to adjust the portfolio weights at the end of month $t-1$ is calculated as

$$x_{t,d} = 0.5 \sum_i |w_{i,t,d} - \widetilde{w}_{i,t-1,d}| \quad \text{with} \quad \widetilde{w}_{i,t-1,d} = \frac{w_{i,t-1,d}(1 + r_{i,t-1})}{\sum_i w_{i,t-1,d}(1 + r_{i,t-1})}. \tag{3}$$

$w_{i,t,d}$ is the weight of stock i in portfolio d immediately after rebalancing at the end of month $t-1$, and $\widetilde{w}_{i,t-1,d}$ is the stock's weight immediately before rebalancing. The latter is calculated based on the initial $t-1$ portfolio weight $w_{i,t-1,d}$ and the stock's return $r_{i,t-1}$ during month $t-1$. End-of-month half-spreads for month t and stock i are calculated as $0.5(Ask_{i,t} - Bid_{i,t})/(0.5(Ask_{i,t} + Bid_{i,t}))$. Portfolio turnover costs result from value-weighting these half-spreads across all stocks in the respective decile portfolio. The strategies' monthly transaction costs are obtained by multiplying turnover and these half-spread costs for both the long and the short decile portfolio (Medhat and Schmeling, 2021).

Due to bid-ask data availability, we estimate transaction costs for the observation period of January 1993 to December 2020. Based on the outlined procedure, average monthly WML transaction costs amount to 0.24% (33.43% winner decile turnover times 0.21% corresponding half-spread plus 36.63% loser decile turnover times 0.46% corresponding half-spread). The momentum strategy's total monthly turnover of 70.06% (33.43% plus 36.63%) is similar to the 74%-estimate of Barroso and Santa-Clara (2015). Given that the HTP formation period is shorter than the MOM formation period by construction, stocks are less likely to appear in the same portfolio in consecutive months. Hence, $rHTP$ requires a higher monthly turnover of 94.59% on average (30.16% for the long decile and 64.43% for the short decile). However, unlike WML, the HTP-strategy does not systematically allocate illiquid stocks to its short leg such that half-spreads are comparably low, resulting in monthly transaction costs of 0.25% for $rHTP$ – very similar to the 0.24% for WML.[13] Referring to the second momentum component PTH, its long-short strategy implies monthly transaction costs of 0.29% on average (71.60% times 0.18% for the long decile plus 32.60% times 0.47% for the short decile).

To conclude, potential trading on $rHTP$ implies transaction costs similar to WML. Given an average monthly $rHTP$ return premium of 0.94% during the inspected subperiod from January 1993 to December 2020, trading costs would not have eliminated the strategy's profits. Beyond its potential relevance for the investment industry, this observation shows that the return spreads documented in Table 1 are not driven by a particularly illiquid stock market segment.

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

So far, we have focused on the time-series properties of $rHTP$ and $rPTH$. In this section, we examine to which extent the two underlying momentum components HTP and PTH

[13]More specifically, the high-HTP (low-HTP) decile goes along with average half-spreads of 0.24% (0.28%). As recent loser stocks tend to trade with less liquidity (Avramov et al., 2016), the trading costs for the WML short leg are comparably high (0.46%). As elaborated in Subsection 4.1, the short leg of $rHTP$ is not strongly tilted toward recent losers such that trading costs are modest (0.28%).

contribute to the overall momentum phenomenon in the cross-section of stock returns. These cross-sectional analyses also allow to control for further stock-level characteristics.

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

To investigate the relationship between HTP, PTH, MOM, and subsequent stock returns $R_{i,t}$, we first run cross-sectional regressions following Fama and MacBeth (1973). In this respect, column (1) in Table 7 shows the time-series averages of coefficients from the cross-sectional regressions $R_{i,t} = \alpha_t + \gamma_{HTP,t} HTP_{i,t-1} + \epsilon_{i,t}$. The average $\gamma_{HTP,t}$-estimate of 1.35 is highly significant and confirms the positive relationship between HTP and subsequent returns. Similarly, the regressions $R_{i,t} = \alpha_t + \gamma_{PTH,t} PTH_{i,t-1} + \epsilon_{i,t}$ support the positive PTH-$R_{i,t}$-relationship (see column (2)). The traditional momentum effect is reflected by $\gamma_{MOM,t}$ obtained from the regressions $R_{i,t} = \alpha_t + \gamma_{MOM,t} MOM_{i,t-1} + \epsilon_{i,t}$. Given that $MOM_{i,t-1} = HTP_{i,t-1} + PTH_{i,t-1}$, the momentum effect $\gamma_{MOM,t}$ is a linear combination of HTP-effect $\gamma_{HTP,t}$ and PTH-effect $\gamma_{PTH,t}$, that is,

$$\gamma_{MOM,t} = \frac{\sigma^2_{HTP,t-1}}{\sigma^2_{MOM,t-1}} \gamma_{HTP,t} + \frac{\sigma^2_{PTH,t-1}}{\sigma^2_{MOM,t-1}} \gamma_{PTH,t}, \tag{4}$$

where $\sigma_{MOM,t-1}$, $\sigma_{HTP,t-1}$, and $\sigma_{PTH,t-1}$ denote the cross-sectional standard deviation of MOM, HTP, and PTH in month $t-1$, respectively.[14] Equation (4) shows that the significant momentum effect in Table 7 stems from the HTP- and PTH-component, and that the volatility-based weights will prove helpful in the following subsection when analyzing how HTP and PTH contribute to the momentum phenomenon across time.

[14]Note that substituting $\gamma_{HTP,t} = Cov(R_{i,t}, HTP_{i,t-1})/\sigma^2_{HTP,t-1}$ and $\gamma_{PTH,t} = Cov(R_{i,t}, PTH_{i,t-1})/\sigma^2_{PTH,t-1}$ in $\gamma_{MOM,t} = Cov(R_{i,t}, MOM_{i,t-1})/\sigma^2_{MOM,t-1} = Cov(R_{i,t}, HTP_{i,t-1})/\sigma^2_{MOM,t-1} + Cov(R_{i,t}, PTH_{i,t-1})/\sigma^2_{MOM,t-1}$ yields Equation (4).

Controlling for further stock-level variables in Table 7, the return predictability of HTP and PTH remains significant after accounting for a stock'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 ($IVOL$).[15] This observation reinforces our argument 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).

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 that also measures a stock's return over the beginning of the momentum formation period. However, while Novy-Marx (2012) uses a fixed six-month horizon to split up MOM, our decomposition approach is dynamic in the sense that it depends on the timing of P_{high}. Table 7 shows that the return predictability of HTP and PTH is not captured by the intermediate momentum return $IMOM$.[16] 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 7 shows that the $IMOM$-coefficient is insignificant. As additional Online Appendix robustness check, we examine long-short returns based on $IMOM$, complementary to Table 1. While $IMOM$ is a

[15] Note that across the different regression specifications, these analyses indicate similar return predictive powers for HTP and PTH. In contrast, the mean of $rHTP$ is considerably higher than the mean of $rPTH$ (see Table 1). The reason is that the Fama-MacBeth-regressions in Table 7 apply *equal*-weighted OLS regressions while $rHTP$ and $rPTH$ are based on *value*-weighted portfolios. The Online Appendix therefore also presents value-weighted Fama-MacBeth-regressions: the resulting regression coefficients are consistently larger for HTP than for PTH.

[16] In untabulated analyses, we also include the return of month $t-12$ as additional predictive variable in Fama-MacBeth-regressions to capture seasonality effects (Heston and Sadka, 2008): HTP remains a significantly positive return predictor.

Table 7. HTP, PTH, and MOM 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 firm'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 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$intercept$	0.80	1.25	1.04	0.88	3.86	3.42	3.55
	(4.03)	(7.04)	(4.94)	(5.36)	(6.43)	(6.05)	(6.27)
HTP	1.35			1.22	1.07	1.18	0.99
	(7.30)			(7.10)	(7.22)	(7.84)	(4.44)
PTH		0.77		0.84	1.57	1.30	1.25
		(2.26)		(2.67)	(6.40)	(5.53)	(4.98)
MOM			0.93				
			(6.28)				
$BETA$					-0.02	-0.00	0.01
					(-0.92)	(-0.08)	(0.26)
$SIZE$					-0.16	-0.13	-0.14
					(-5.61)	(-4.97)	(-5.14)
BM					0.13	0.09	0.09
					(5.38)	(4.27)	(4.25)
$ILLIQ$						0.02	0.02
						(3.46)	(3.54)
REV						-0.06	-0.06
						(-13.31)	(-13.22)
$IVOL$						-0.77	-0.77
						(-4.57)	(-4.68)
$IMOM$							0.28
							(1.33)

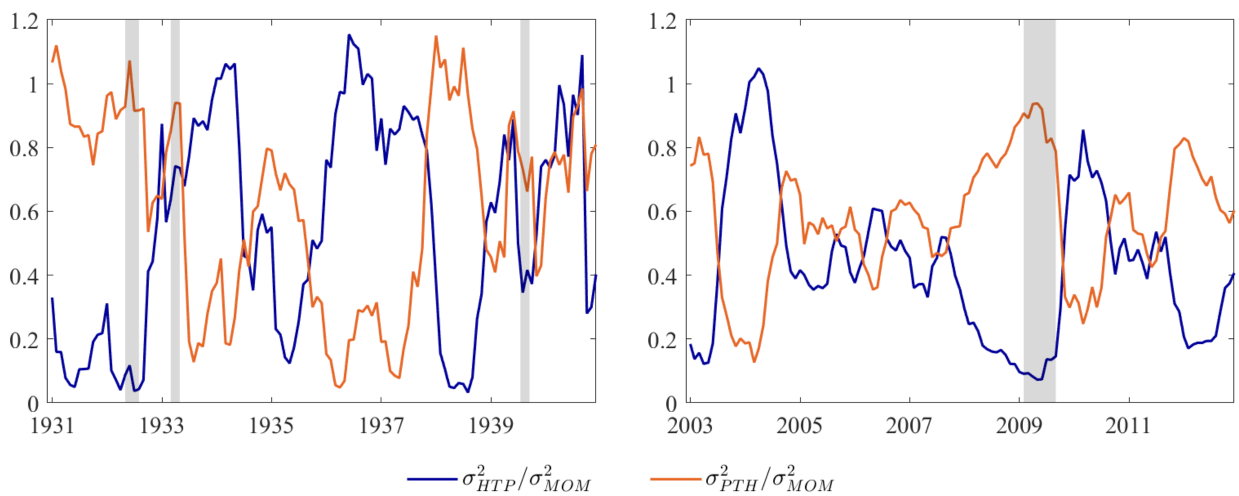
significant return predictor, the corresponding return spread is slightly smaller compared to HTP. More importantly, the $IMOM$-based long-short strategy yields negatively skewed returns and is prone to severe crash risk (e.g., minimum monthly return of -90.66% compared with -32.80% for $rHTP$). Consequently, in line with our arguments in Section 4, it is the flexible MOM formation period decomposition based on P_{high} that allows $rHTP$ to alleviate momentum crash risk.

6.2. Contribution of HTP and PTH to Momentum Effect

The cross-sectional regressions in the previous subsection show that both HTP and PTH (by construction) contribute to the overall momentum effect. 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 WML is prone to similar crashes as $rPTH$ and does not substantially profit from the crash-resilient nature of $rHTP$. 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 (4), the relative importance of γ_{HTP} and γ_{PTH} for the momentum effect γ_{MOM} is given by the weights $\sigma^2_{HTP}/\sigma^2_{MOM}$ and $\sigma^2_{PTH}/\sigma^2_{MOM}$, respectively.[17] During the overall sample period, γ_{HTP} and γ_{PTH} contribute to γ_{MOM} to a similar extent: the time-series averages of $\sigma^2_{HTP}/\sigma^2_{MOM}$ and $\sigma^2_{PTH}/\sigma^2_{MOM}$ are 0.4989 and 0.5078, 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 (gray bars), γ_{MOM} disproportionately depends on γ_{PTH} as opposed to γ_{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 determined almost exclusively by the PTH-component. Hence, as $rPTH$ crashes, WML crashes as well and does not benefit from the crash-resilient nature of $rHTP$.

[17]Note that, for simplicity, we suppress time subscripts in this subsection.

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 (4) that determine the contribution of γ_{HTP} and γ_{PTH} to the momentum effect γ_{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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 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}.[18] 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. Conversely, the elimination of PTH from MOM allows a substantial reduction in crash risk.

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

7. Evidence from International Equity Markets

The momentum strategy has been shown to yield significant abnormal returns beyond the US. Researchers found momentum returns in both emerging and developed markets (Rouwenhorst, 1999; Griffin et al., 2010; Jacobs, 2016), in Europe (Rouwenhorst, 1998), North America and Asia (Fama and French, 2012), as well as in numerous country-specific markets (Chan et al., 2000; Griffin et al., 2005; Asness et al., 2013; Daniel and Moskowitz, 2016). Another recurrent finding is that the momentum strategy does not yield significant returns in Japan (Griffin et al., 2005; Fama and French, 2012; Asness et al., 2013). We therefore transfer our analyses to several international equity markets to substantiate our US results. We present summary statistics of WML, $rHTP$, and $rPTH$ for seven different equity markets: Europe (without the UK), the Asia and Pacific region (without Japan), the Americas (without the US), UK, Japan, and two global markets that comprise all the aforementioned markets (either with or without the US).[19] In total, these markets comprise equity data from 37 different countries.

We obtain data on the non-US equity markets from Datastream. We only include primary quotes of common stocks traded on the major exchange in their home country in local currency.[20] By including only common stocks, we exclude non-common equities such as warrants, unit trusts, preferred stocks, American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds, and exchange-traded funds. This data

[19] Market classifications are sourced from MSCI (`https://www.msci.com/index-country-membership-tool`). Europe ex UK comprises Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and Switzerland. Asia Pacific ex Japan includes Australia, China, Hong Kong, India, Indonesia, Malaysia, New Zealand, Pakistan, the Philippines, Singapore, South Korea, Taiwan, and Thailand. Americas ex US comprises Argentina, Brazil, Canada, Chile, Colombia, Mexico, and Peru.

[20] We define the country's major exchange as the one with the most listings. If there are two exchanges of comparable size, we include both in the sample. This is the case for China (Shanghai and Shenzen), India (BSE and NSE), and Japan (Osaka and Tokyo).

Table 8. International Evidence on Monthly Long-Short Returns WML, $rHTP$, and $rPTH$
This table displays summary statistics for the monthly long-short portfolio returns WML, $rHTP$, and $rPTH$ in international stock markets. For each month t, the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Returns are based on local currencies while value-weighting across different currencies is based on exchange rates at the end of month $t-1$. Stocks are allocated to these decile portfolios based on MOM, HTP, and PTH at the end of each month $t-1$. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
Europe ex UK, Jan 1974 - Dec 2020												
WML	1.44	4.26	8.74	0.57	-0.45	6.58	-77.78	-37.77	-2.91	1.45	6.37	43.50
$rHTP$	1.36	4.60	6.40	0.73	0.32	5.45	-59.04	-24.08	-2.52	1.24	4.76	30.89
$rPTH$	0.76	2.37	9.08	0.29	-0.81	8.85	-77.86	-53.31	-3.39	1.26	5.34	46.16
Asia and Pacific ex Japan, Jan 1974 - Dec 2020												
WML	0.74	1.51	11.90	0.22	-1.27	14.33	-98.98	-98.27	-4.09	1.84	6.61	69.02
$rHTP$	1.13	3.02	9.61	0.41	0.28	8.64	-86.43	-36.75	-3.48	1.79	6.21	69.44
$rPTH$	0.30	0.63	11.53	0.09	-1.65	12.25	-99.52	-93.09	-4.08	1.43	6.51	34.11
Americas ex US, Feb 1977 - Dec 2020												
WML	2.36	4.49	11.30	0.72	-0.22	5.11	-83.74	-49.13	-3.22	2.51	8.78	56.31
$rHTP$	2.09	4.55	9.83	0.74	1.70	18.77	-69.28	-32.94	-3.35	1.71	6.56	95.43
$rPTH$	1.33	2.37	11.30	0.41	-0.49	4.96	-86.06	-49.43	-4.38	2.04	7.71	40.95
UK, Jan 1966 - Dec 2020												
WML	1.31	3.58	9.87	0.46	-0.49	7.65	-76.86	-65.44	-3.81	1.48	6.48	46.11
$rHTP$	1.25	4.07	7.79	0.56	0.13	6.37	-73.31	-36.50	-3.19	1.34	5.96	48.07
$rPTH$	0.46	1.17	9.57	0.16	-0.90	8.08	-87.09	-63.93	-4.36	0.84	5.44	34.92
Japan, Jan 1974 - Dec 2020												
WML	0.37	1.14	7.97	0.16	-0.47	6.48	-73.92	-42.20	-3.49	0.50	4.66	31.03
$rHTP$	0.77	2.50	6.58	0.40	0.49	5.89	-53.87	-23.50	-3.14	0.51	4.40	34.00
$rPTH$	0.02	0.07	7.82	0.01	-0.49	5.12	-89.27	-38.16	-3.87	0.56	4.49	25.34
Global ex US, Jan 1974 - Dec 2020												
WML	0.79	2.04	8.62	0.32	-0.80	6.15	-75.53	-43.11	-3.49	1.43	5.76	31.62
$rHTP$	1.00	3.48	6.59	0.53	-0.25	6.43	-70.60	-27.57	-2.25	1.30	4.78	37.03
$rPTH$	0.21	0.52	8.60	0.08	-0.88	6.58	-95.83	-43.74	-3.60	0.75	4.92	26.50
Global with US, Jan 1974 - Dec 2020												
WML	1.13	3.53	7.90	0.50	-1.03	7.26	-76.88	-46.23	-2.63	1.72	5.52	24.93
$rHTP$	1.21	4.20	6.12	0.69	-0.32	5.82	-71.22	-29.46	-1.97	1.58	4.69	26.55
$rPTH$	0.86	2.52	8.03	0.37	-1.00	7.48	-75.51	-45.20	-2.65	1.56	4.75	26.59

selection procedure follows the standard in global equity research (Ince and Porter, 2006; Griffin et al., 2010; Jacobs, 2016; Cakici and Zaremba, 2022).

We consider both active and dead stocks to avoid survivorship bias and delete zero returns due to stale prices erroneously reported by Datastream after a stock's delisting (Ince and Porter, 2006). To prevent data errors, we follow Griffin et al. (2010) and Ince and Porter (2006) and apply the following return filters. If a daily return is larger than 100% and is reversed within one day, we treat the returns on these two days as missing. Furthermore, any daily return exceeding 200% is set to missing. Regarding monthly returns, if a return exceeds 300% and is reversed within one month, we set the two corresponding monthly returns equal to missing. Additionally, we set all monthly returns larger than 500% equal to missing (Cakici and Zaremba, 2022). For the computation of MOM, HTP, and PTH, we require at least 100 non-zero return days in the previous year and 12 valid monthly returns. We thereby exclude stocks that are not actively traded from the sample. We also exclude stock-month observations if the stock's market capitalization is missing. To ensure that a country's results are not driven by only a few stocks, we require at least 25 actively traded stocks for a month-country combination to be included in the sample.

After applying these filters, we end up with a sample starting in January 1966 for the UK, in February 1977 for the Americas ex US, and in January 1974 for all other countries. The sample period for the global portfolios also starts in January 1974 to avoid results driven by the longer sample period of the UK data. All sample periods end in December 2020. The international analyses are based on a total of 8,102,091 stock-month observations.

Summary statistics of WML, $rHTP$, and $rPTH$ for the different international equity markets are presented in Table 8. We find significantly positive monthly returns of the HTP-based strategy in each of the seven international stock markets that we consider – even in Japan, where standard momentum strategies have been documented to be insignificant (Griffin et al., 2005; Fama and French, 2012; Asness et al., 2013). Correspondingly, WML does not yield significant return premiums in Japan and the Asia and Pacific region. The PTH-strategy is only significant in Europe, the Americas, and the global market. Regarding the strategies' crash risk, WML and $rPTH$ are consistently more left-skewed than $rHTP$. In each market, this goes hand in hand with less extreme maximum drawdowns and minimum monthly returns for $rHTP$ compared with the other two strategies. Furthermore, $rHTP$ offers a higher Sharpe ratio than WML and $rPTH$ in every market.

8. 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 essentially unskewed and not dependent on market states. As a crash-resilient alternative to traditional momentum, HTP yields similar long-short returns on average and an even higher Sharpe ratio. Our 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 literature on the 52-week high, the driving forces of 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.

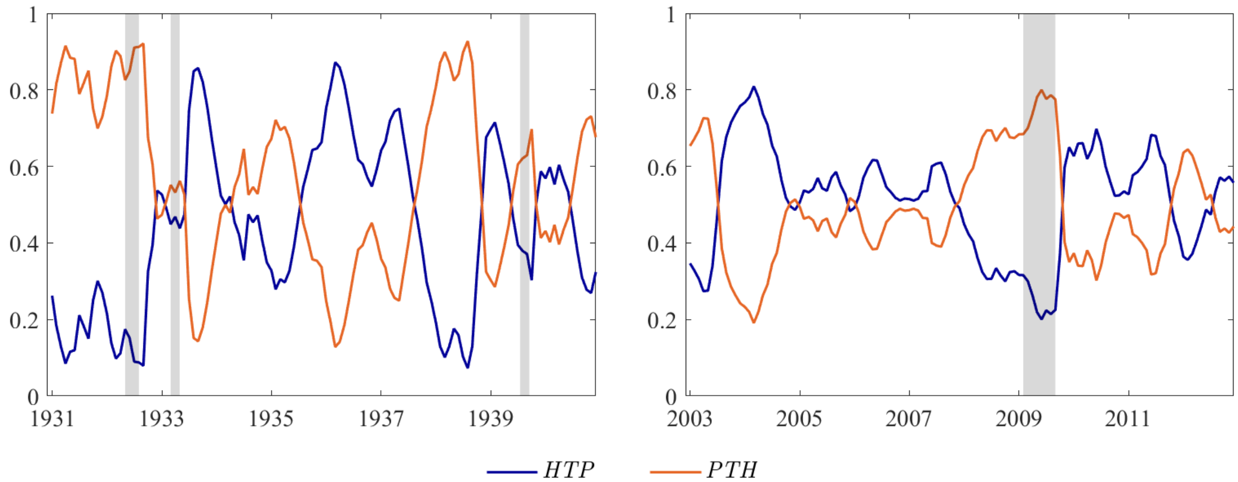


Table A1. Decile Portfolio Sorts Based on *MOM*, *HTP*, and *PTH*
This table reports monthly value- and equal-weighted portfolio sorts based on MOM, HTP, and PTH. MOM is the stock's log return over formation months $t-12$ to $t-2$. HTP refers to the return component of MOM realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

	MOM				HTP				PTH			
	value		equal		value		equal		value		equal	
	raw	α_{FF3}	*raw*	α_{FF3}	*raw*	α_{FF3}	*raw*	α_{FF3}	*raw*	α_{FF3}	*raw*	α_{FF3}
low	0.35	-1.12	0.98	-0.63	0.45	-0.49	0.64	-0.54	0.56	-1.08	1.27	-0.45
2	0.73	-0.56	1.12	-0.32	0.71	-0.19	0.82	-0.32	0.79	-0.68	1.27	-0.32
3	0.77	-0.37	1.11	-0.20	0.82	-0.13	1.04	-0.12	0.97	-0.35	1.35	-0.09
4	0.90	-0.17	1.23	-0.06	0.89	-0.05	1.15	-0.06	1.05	-0.14	1.40	0.07
5	0.91	-0.10	1.22	0.02	1.05	0.08	1.24	0.01	1.08	-0.04	1.37	0.12
6	0.95	-0.05	1.31	0.15	1.04	0.04	1.29	0.07	0.97	-0.08	1.39	0.23
7	1.02	0.09	1.34	0.22	1.11	0.10	1.41	0.14	1.01	0.02	1.40	0.31
8	1.13	0.23	1.44	0.35	1.20	0.16	1.45	0.18	1.05	0.16	1.36	0.35
9	1.20	0.29	1.57	0.50	1.34	0.25	1.72	0.36	0.98	0.14	1.32	0.39
high	1.53	0.61	1.79	0.69	1.66	0.51	1.89	0.48	1.03	0.29	1.39	0.55
10-1	1.18	1.73	0.81	1.32	1.21	1.01	1.24	1.02	0.48	1.37	0.12	1.00
t(10-1)	(5.45)	(9.57)	(3.68)	(7.28)	(6.59)	(5.72)	(7.35)	(6.88)	(1.82)	(8.32)	(0.40)	(5.21)

Table A2. Monthly Long-Short Returns WML, $rHTP$, and $rPTH$ in Subperiods
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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020 and is split into four periods of equal size for this analysis.

Panel A: January 1927 to June 1950

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	0.99	1.78	10.72	0.32	-2.56	17.62	-95.35	-77.56	-2.36	1.43	6.22	25.83
$rHTP$	1.56	3.76	7.05	0.76	0.04	8.46	-57.53	-32.80	-2.12	1.36	4.87	35.36
$rPTH$	-0.36	-0.50	13.07	-0.10	-2.52	15.31	-99.88	-83.40	-3.81	1.27	5.55	33.34

Panel B: July 1950 to December 1973

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.62	6.43	4.82	1.17	-0.53	5.00	-28.13	-18.52	-1.06	1.76	4.42	14.68
$rHTP$	1.14	4.43	4.40	0.89	0.07	5.02	-27.90	-16.36	-1.32	0.86	3.67	19.79
$rPTH$	1.12	3.79	4.84	0.80	-0.81	6.35	-30.42	-23.16	-1.16	1.40	3.71	14.16

Panel C: January 1974 to June 1997

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.40	4.86	5.10	0.95	-0.82	5.22	-29.68	-19.03	-0.86	1.78	4.41	16.21
$rHTP$	1.21	3.88	4.92	0.85	-0.26	4.16	-39.18	-16.09	-1.36	1.03	4.36	18.05
$rPTH$	0.74	2.75	5.14	0.50	-1.26	6.77	-41.16	-26.91	-1.50	1.31	3.89	14.62

Panel D: July 1997 to December 2020

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	0.72	1.34	9.15	0.27	-1.27	7.92	-81.19	-45.10	-2.75	1.33	5.28	25.41
$rHTP$	0.92	2.09	6.34	0.50	0.22	7.41	-66.91	-28.86	-2.07	0.59	4.17	31.67
$rPTH$	0.40	0.68	9.59	0.15	-1.18	7.44	-86.11	-44.22	-3.61	1.23	5.01	28.57

Table A3. Monthly Long-Short Returns *WML*, *rHTP*, and *rPTH* (Jul 1963 to Dec 2020)
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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 July 1963 to December 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.24	4.65	7.12	0.60	-1.38	9.98	-81.19	-45.10	-1.49	1.67	4.97	25.41
$rHTP$	1.12	4.73	5.62	0.69	0.02	6.52	-66.91	-28.86	-1.70	0.94	4.27	31.67
$rPTH$	0.70	2.45	7.35	0.33	-1.39	9.98	-86.11	-44.22	-2.27	1.39	4.22	28.57

Table A4. 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 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML	1.18	5.45	7.87	0.52	-2.26	19.36	-95.35	-77.56	-1.74	1.54	5.06	25.83
$WML_{t-12,t-7}$	1.03	5.22	6.68	0.53	-3.56	46.02	-97.17	-90.66	-1.72	1.32	3.96	26.92
$WML_{t-6,t-2}$	0.60	2.45	7.27	0.29	-2.53	20.65	-99.20	-66.89	-2.25	1.12	4.22	27.82

Table A5. Volatility-Based Subperiod Analysis of Long-Short Returns WML, $rHTP$, and $rPTH$
This table shows average monthly long-short portfolio returns WML, $rHTP$, and $rPTH$ for high versus low volatility state. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. Following Barroso and Santa-Clara (2015), at the end of each month $t-1$, we calculate the volatility of the daily long-short returns WML, $rHTP$, and $rPTH$ over the previous 126 trading days. Following Barroso and Wang (2021), month t is classified as high (low) volatility month in the analysis of WML, $rHTP$, and $rPTH$ if the respective volatility is above (below) its 70% (30%) time-series percentile. Unlike Barroso and Wang (2021), however, we consider the volatility of the long-short returns of the respective momentum strategies and not the WML volatility in general. 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 volatility subperiods. The corresponding t-statistics are based on two-sample t-tests (Welch's t-test with unequal variances). The sample period covers July 1927 to December 2020 as we need six months of long-short returns to classify months.

	WML		$rHTP$		$rPTH$	
Volatility	Low	High	Low	High	Low	High
mean	2.24	0.46	1.06	1.22	1.19	-0.36
t	(9.80)	(0.79)	(5.10)	(2.55)	(4.80)	(-0.49)
Δ	1.78		-0.16		1.55	
t	(2.81)		(-0.31)		(2.02)	

Table A6. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020. We exclude the ten most extreme momentum crash months considered in Table 2 from the paper here.

	Correlation Coefficient					t-statistics				
	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$	WML	WML_{LL}	WML_{SL}	$rHTP$	$rPTH$
WML	1.00									
WML_{LL}	0.70	1.00				32.65				
WML_{SL}	0.82	0.16	1.00			47.43	5.40			
$rHTP$	0.42	0.74	-0.02	1.00		15.37	37.26	-0.75		
$rPTH$	0.70	0.16	0.84	-0.17	1.00	32.59	5.38	50.88	-5.77	

Table A7. Intercept and Slope Estimates from Factor Spanning Tests for WML, $rHTP$, and $rPTH$
This table displays intercept and slope estimates from time-series regressions based on monthly data with the long-short returns WML, $rHTP$, and $rPTH$ as dependent variables. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The independent variables are based on the market factor (January 1927 to December 2020), the Fama and French (1993) three-factor model (January 1927 to December 2020), the Fama and French (2015) five-factor model (July 1963 to December 2020), the Fama and French (2018) six-factor model including a momentum factor (July 1963 to December 2020), the Hou et al. (2015) q-factor model (January 1967 to December 2020), the Barillas and Shanken (2018) six-factor model (January 1967 to December 2020), the Stambaugh and Yuan (2017) mispricing-factor model (January 1963 to December 2016), and the Daniel et al. (2020) behavioral factor model (July 1972 to December 2020). While α represents the intercept estimate, the reported slope coefficients are based on the following factors: MKT, SMB, HML, RMW, CMA, and UMD denote the excess market return as well as the long-short returns associated with firm size, book-to-market, operating profitability, investments, and momentum, respectively, and are obtained from Kenneth R. French's website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`). q_{ME}, q_{IA}, and q_{ROE} are the long-short returns associated with firm size, investment-to-assets, and profitability obtained from `http://global-q.org/factors.html`. HML_m is the long-short return associated with book-to-market as defined in Asness and Frazzini (2013) and sourced from `https://www.aqr.com/Insights/Datasets/The-Devil-in-HMLs-Details-Factors-Monthly`. The factors SMB_S, $MGMT$, and $PERF$ represent the long-short returns associated with firm size, management, and performance obtained from Robert F. Stambaugh's website (`https://finance.wharton.upenn.edu/~stambaug/`), and FIN and $PEAD$ are the short- and long-horizon behavioral factors obtained from Kent Daniel's website (`http://www.kentdaniel.net/data.php`). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: WML as Dependent Time-Series

Model	α	MKT	SMB	HML	RMW	CMA	UMD	q_{ME}	q_{IA}	q_{ROE}	HML_m	SMB_S	$MGMT$	$PERF$	FIN	$PEAD$
MKT	1.56	-0.55														
t	(8.81)	(-3.67)														
FF3	1.73	-0.39	-0.22	-0.73												
t	(9.57)	(-4.16)	(-1.68)	(-4.26)												
FF5	1.39	-0.32	0.01	-0.81	0.42	0.51										
t	(4.18)	(-2.83)	(0.05)	(-3.27)	(1.17)	(1.25)										
FF6	0.33	-0.09	-0.06	-0.03	0.08	0.00	1.52									
t	(2.99)	(-1.99)	(-0.95)	(-0.44)	(0.86)	(0.00)	(46.03)									
q	0.59	-0.23						0.26	-0.16	1.46						
t	(1.62)	(-2.34)						(1.13)	(-0.48)	(6.48)						
BS6	0.37	-0.10	-0.06				1.44		0.01	0.09	-0.10					
t	(2.92)	(-2.13)	(-1.08)				(29.07)		(0.15)	(1.05)	(-1.10)					
SY	0.11	0.08										0.14	0.29	1.34		
t	(0.47)	(1.28)										(1.08)	(2.06)	(13.88)		
DHS	0.08	-0.21													1.82	0.12
t	(0.26)	(-1.67)													(8.28)	(0.68)

(continued)

Table A7. Continued

Panel B: *rHTP* as Dependent Time-Series

Model	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*UMD*	q_{ME}	q_{IA}	q_{ROE}	HML_m	SMB_S	*MGMT*	*PERF*	*FIN*	*PEAD*
MKT	0.97	0.34														
t	(5.04)	(3.40)														
FF3	1.01	0.29	0.55	-0.35												
t	(5.72)	(4.32)	(5.97)	(-3.22)												
FF5	1.16	0.20	0.44	-0.48	-0.24	-0.24										
t	(5.00)	(3.15)	(3.21)	(-3.19)	(-1.11)	(-1.07)										
FF6	0.59	0.32	0.41	-0.06	-0.42	-0.52	0.82									
t	(3.73)	(6.71)	(4.46)	(-0.47)	(-3.64)	(-2.91)	(8.76)									
q	0.79	0.28						0.50	-0.61	0.37						
t	(2.81)	(4.46)						(3.30)	(-2.52)	(2.29)						
BS6	0.63	0.37	0.35				0.88		-0.38	-0.44	-0.10					
t	(3.55)	(7.64)	(3.98)				(9.53)		(-2.67)	(-3.77)	(-0.81)					
SY	0.57	0.33										0.53	-0.45	0.57		
t	(2.83)	(5.43)										(4.43)	(-2.74)	(6.18)		
DHS	0.56	0.29													1.01	-0.44
t	(2.80)	(4.81)													(5.60)	(-3.18)

Panel C: *rPTH* as Dependent Time-Series

Model	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*UMD*	q_{ME}	q_{IA}	q_{ROE}	HML_m	SMB_S	*MGMT*	*PERF*	*FIN*	*PEAD*
MKT	1.17	-1.02														
t	(6.31)	(-9.52)														
FF3	1.37	-0.75	-0.94	-0.58												
t	(8.32)	(-9.71)	(-8.22)	(-3.82)												
FF5	0.96	-0.62	-0.62	-0.51	0.64	0.71										
t	(3.72)	(-6.50)	(-3.86)	(-2.59)	(1.94)	(2.14)										
FF6	0.21	-0.45	-0.67	0.04	0.40	0.35	1.08									
t	(1.43)	(-8.27)	(-8.51)	(0.50)	(3.01)	(2.48)	(18.87)									
q	0.31	-0.57						-0.36	0.40	1.34						
t	(1.16)	(-7.81)						(-1.93)	(1.48)	(7.10)						
BS6	0.19	-0.49	-0.64				0.98		0.31	0.39	0.01					
t	(1.15)	(-9.32)	(-7.85)				(15.95)		(2.39)	(3.12)	(0.06)					
SY	-0.06	-0.25										-0.50	0.79	1.05		
t	(-0.27)	(-3.88)										(-5.19)	(9.84)	(12.72)		
DHS	-0.41	-0.53													1.57	0.67
t	(-1.46)	(-5.23)													(8.22)	(5.35)

Table A8. Factor Spanning Tests for WML, $rHTP$, and $rPTH$ – Fixed Sample Period
This table displays intercepts α from time-series regressions based on monthly data with the long-short returns WML, $rHTP$, and $rPTH$ as dependent variables. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The independent variables are based on the market factor, the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, the Fama and French (2018) six-factor model including a momentum factor, the Hou et al. (2015) q-factor model, the Barillas and Shanken (2018) six-factor model, the Stambaugh and Yuan (2017) mispricing-factor model, and the Daniel et al. (2020) behavioral factor model. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers July 1972 to December 2016.

	raw	α_{MKT}	α_{FF3}	α_{FF5}	α_{FF6}	α_q	α_{BS6}	α_{SY}	α_{DHS}
WML	1.18	1.37	1.65	1.32	0.23	0.42	0.23	0.03	0.04
t	(5.45)	(4.76)	(6.01)	(3.14)	(1.74)	(0.99)	(1.66)	(0.10)	(0.12)
$rHTP$	1.21	0.79	1.05	1.17	0.58	0.75	0.60	0.58	0.64
t	(6.59)	(2.88)	(4.33)	(4.23)	(3.31)	(2.28)	(3.08)	(2.53)	(2.90)
$rPTH$	0.48	1.22	1.35	0.92	0.14	0.21	0.08	-0.15	-0.49
t	(1.82)	(4.40)	(5.96)	(2.86)	(0.84)	(0.67)	(0.45)	(-0.66)	(-1.65)

Table A9. HTP, PTH, and MOM 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
intercept	0.53	0.99	0.67	0.60	1.15	2.05	2.16
	(3.50)	(6.77)	(4.58)	(4.41)	(2.46)	(4.09)	(4.44)
HTP	1.75			1.69	1.63	1.86	1.68
	(6.83)			(6.48)	(7.09)	(8.01)	(5.19)
PTH		1.17		1.18	1.33	0.98	1.01
		(2.96)		(3.13)	(4.16)	(3.19)	(3.21)
MOM			1.31				
			(7.02)				
$BETA$					-0.04	-0.02	-0.01
					(-1.12)	(-0.50)	(-0.36)
$SIZE$					-0.03	-0.06	-0.06
					(-1.41)	(-2.95)	(-3.24)
BM					0.13	0.10	0.10
					(2.64)	(2.02)	(1.98)
$ILLIQ$						0.01	0.01
						(2.12)	(2.00)
REV						-0.03	-0.03
						(-6.81)	(-7.14)
$IVOL$						-1.40	-1.37
						(-5.81)	(-5.98)
$IMOM$							0.22
							(0.67)

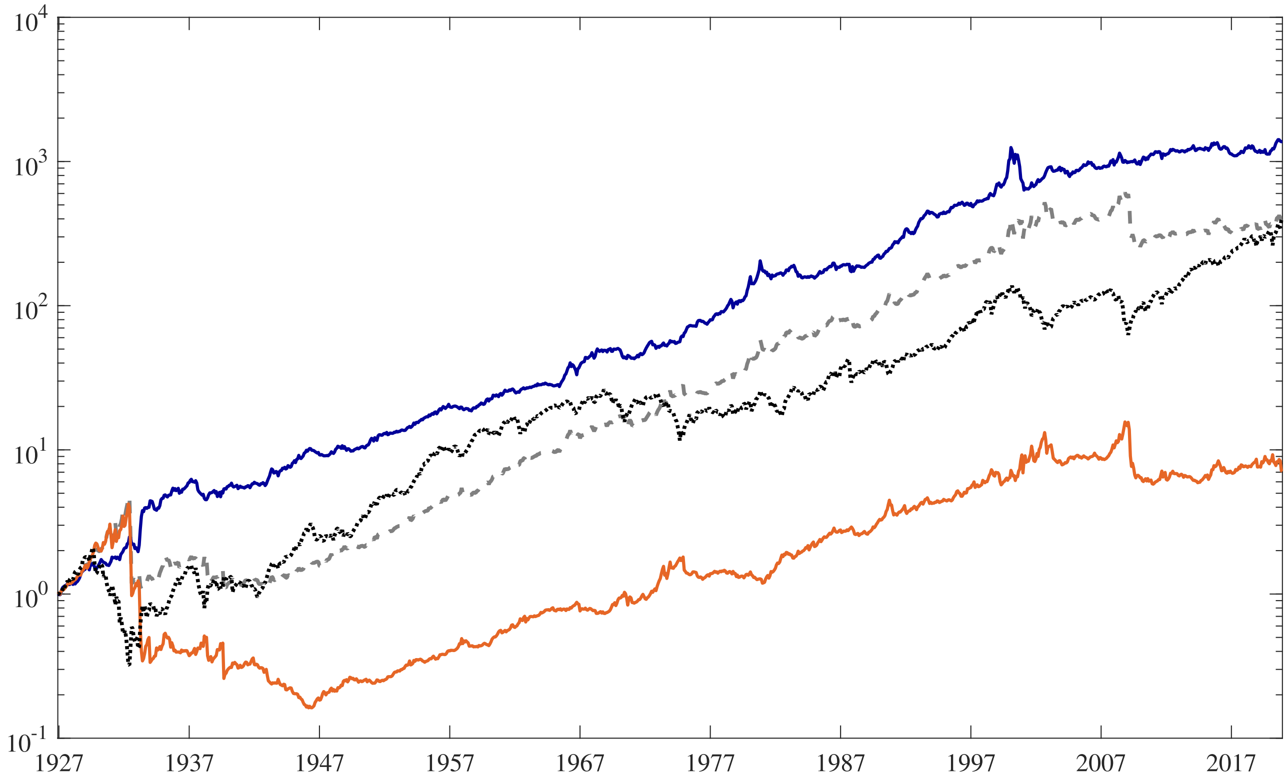
Table A10. Monthly Long-Short Returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

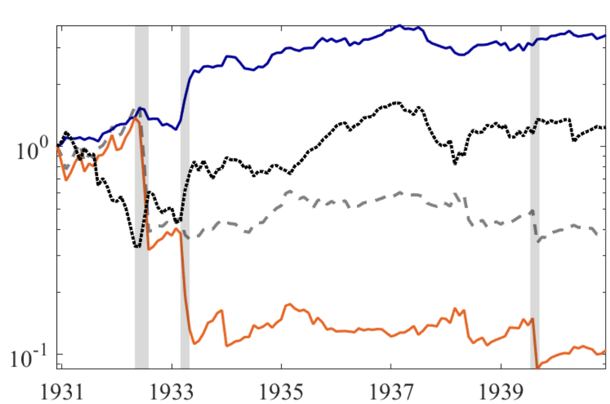
	mean	t(mean)	std	SR	skew	kurt	maxDD	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
WML^{FF}	0.65	4.82	4.75	0.47	-3.15	32.52	-78.23	-54.00	-0.99	0.79	2.88	18.24
$rHTP^{FF}$	0.70	6.08	3.35	0.72	0.86	11.79	-49.35	-17.43	-0.96	0.62	2.42	28.47
$rPTH^{FF}$	0.35	2.10	5.50	0.22	-3.32	29.32	-96.15	-53.19	-1.31	0.78	2.59	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.

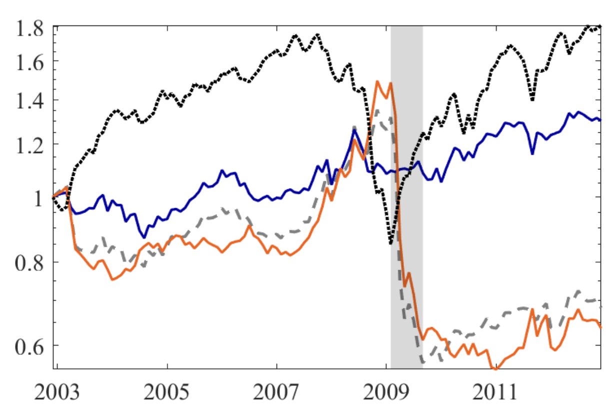
Panel A: January 1927 to December 2020



Panel B: January 1931 to December 1940



Panel C: January 2003 to December 2012



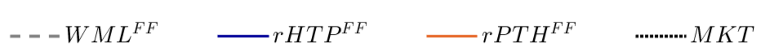


Table A11. Most Extreme Momentum Crash Months
This table shows WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ for those ten months t in the sample period that show the most negative return WML^{FF}. We construct the long-short returns WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ according to the UMD momentum factor 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

month	WML^{FF}	$rHTP^{FF}$	$rPTH^{FF}$	MKT	MKT_{24m}
Aug 1932	-54.00	-10.42	-53.19	37.06	-68.46
Jul 1932	-46.22	-0.86	-47.60	33.84	-75.47
Apr 2009	-34.99	0.89	-34.52	10.18	-43.51
Sep 1939	-30.34	6.89	-43.16	16.88	-21.62
Jan 2001	-25.32	-3.27	-25.01	3.13	-0.28
Jun 1938	-23.66	3.07	-25.56	23.87	-28.23
Jun 1931	-18.34	-2.60	-17.20	13.90	-50.52
Apr 1933	-17.03	28.47	-49.75	38.85	-59.65
Nov 2002	-16.33	3.97	-19.42	5.96	-40.13
Jan 1975	-13.64	5.77	-19.02	13.66	-49.72

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The sample period covers January 1927 to December 2020.

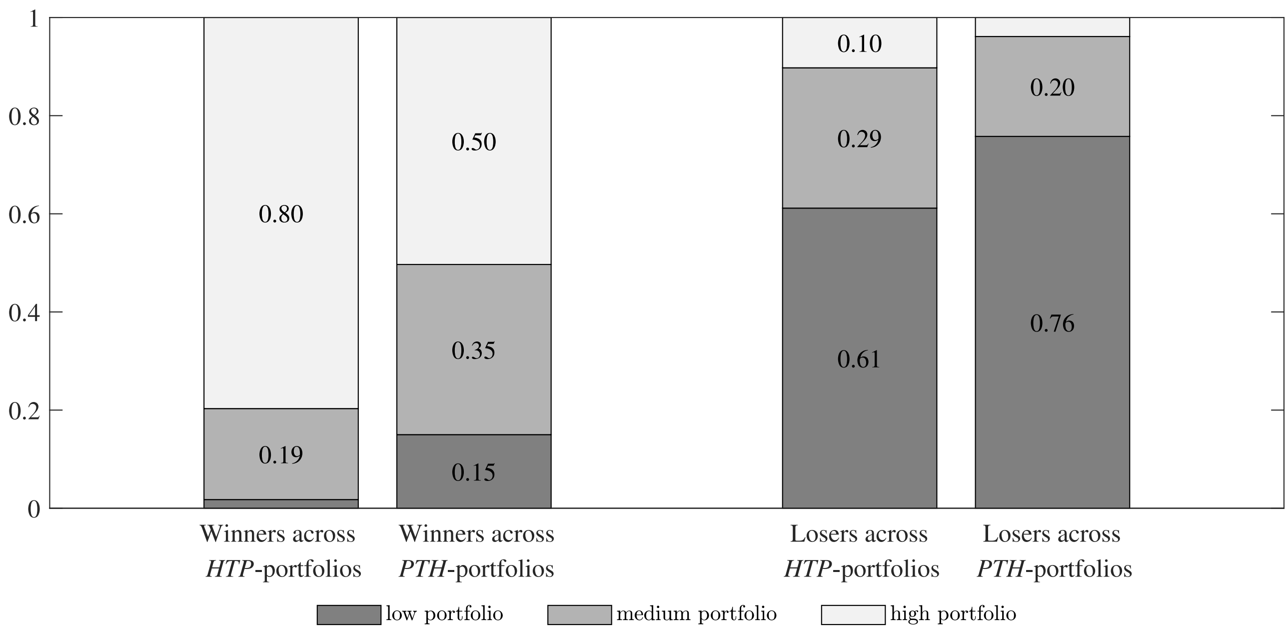


Table A12. Correlation of WML^{FF}, WML^{FF}_{LL}, WML^{FF}_{SL}, $rHTP^{FF}$, and $rPTH^{FF}$

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 2020.

	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				49.61				
WML^{FF}_{SL}	0.88	0.46	1.00			62.43	17.59			
$rHTP^{FF}$	0.42	0.62	0.14	1.00		15.46	26.33	4.73		
$rPTH^{FF}$	0.78	0.46	0.85	-0.14	1.00	42.40	17.46	54.03	-4.77	

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. Loser stocks as well as low-HTP portfolios (low-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. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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.

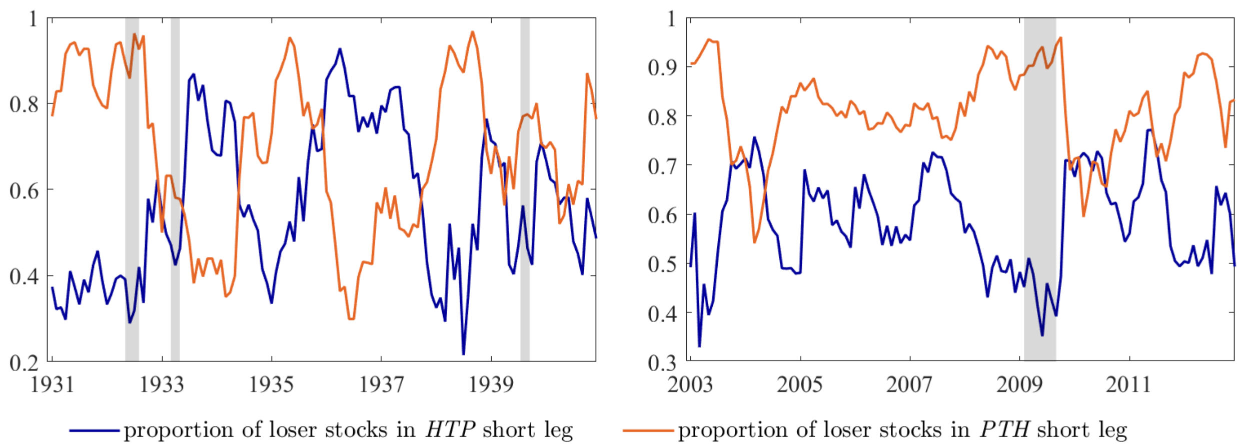


Table A13. Time Varying Market Betas and Optionality of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$
This table shows regression coefficients for the time-series regression $WML_t^{FF} = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t$. In alternative specifications, $rHTP^{FF}$ 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 are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers July 1928 to December 2020 as we need 24 months of market returns to define the bear market dummy.

	WML^{FF}			$rHTP^{FF}$			$rPTH^{FF}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
α_0	0.84	0.88	0.88	0.52	0.40	0.40	0.78	0.93	0.93
t	(7.48)	(8.17)	(8.17)	(4.70)	(3.71)	(3.71)	(6.75)	(8.66)	(8.66)
α_B		-1.05	0.62		0.49	-0.09		-1.55	0.91
t		(-2.38)	(0.82)		(1.49)	(-0.13)		(-3.03)	(1.74)
β_0	-0.31	0.01	0.01	0.26	0.34	0.34	-0.67	-0.42	-0.42
t	(-2.97)	(0.20)	(0.20)	(4.51)	(8.40)	(8.40)	(-7.88)	(-9.39)	(-9.38)
β_B		-0.70	-0.39		-0.19	-0.29		-0.55	-0.10
t		(-5.46)	(-4.07)		(-1.69)	(-3.85)		(-5.66)	(-1.32)
$\beta_{B,R}$			-0.52			0.18			-0.77
t			(-2.04)			(0.80)			(-6.25)

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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.

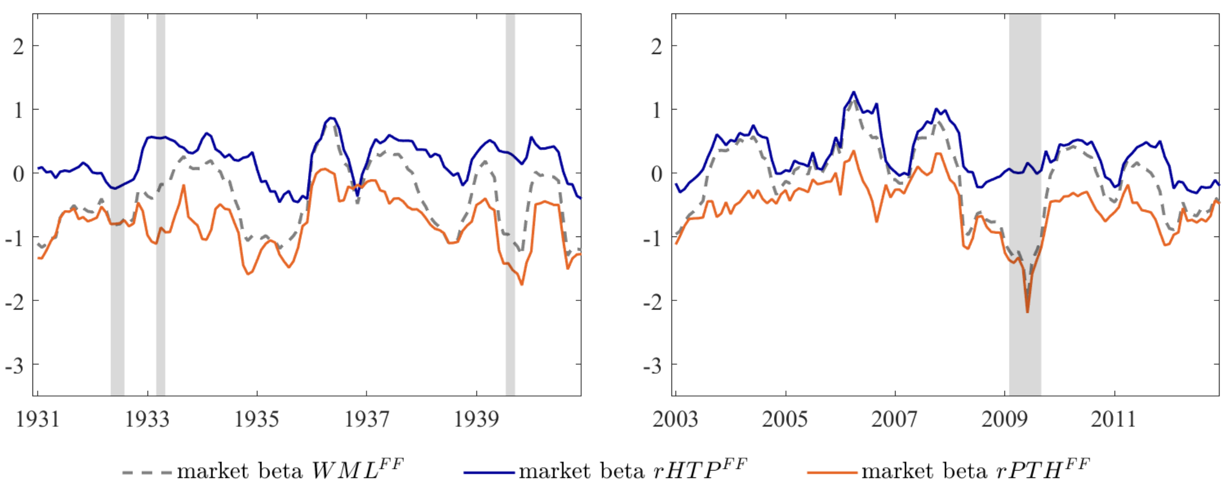


Table A14. Subperiod Analyses of WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$

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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM 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 July 1929 to December 2020 for the market state analyses, as we need 36 months of market returns to classify months, and January 1927 to December 2020 for the return dispersion analyses.

	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	0.82	-0.42	0.96	0.34	0.60	1.06	0.62	0.78	0.60	-1.17	0.87	-0.16
t	(7.47)	(-0.71)	(7.21)	(1.36)	(5.12)	(2.79)	(4.98)	(3.92)	(4.96)	(-1.55)	(6.65)	(-0.52)
Δ	1.23		0.63		-0.47		-0.16		1.77		1.02	
t	(2.08)		(2.22)		(-1.17)		(-0.68)		(2.32)		(3.10)	

Table A15. Factor Spanning Tests for WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$

This table displays intercepts α from time-series regressions based on monthly data with WML^{FF}, $rHTP^{FF}$, and $rPTH^{FF}$ as dependent variables. 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 realized before the formation period's highest stock price, P_{high}. PTH refers to the return component of MOM realized after the formation period's highest stock price, P_{high}. The independent variables are based on the market factor (January 1927 to December 2020), the Fama and French (1993) three-factor model (January 1927 to December 2020), the Fama and French (2015) five-factor model (July 1963 to December 2020), the Fama and French (2018) six-factor model including a momentum factor (July 1963 to December 2020), the Hou et al. (2015) q-factor model (January 1967 to December 2020), the Barillas and Shanken (2018) six-factor model (January 1967 to December 2020), the Stambaugh and Yuan (2017) mispricing-factor model (January 1963 to December 2016), and the Daniel et al. (2020) behavioral factor model (July 1972 to December 2020). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	raw	α_{MKT}	α_{FF3}	α_{FF5}	α_{FF6}	α_{q}	α_{BS6}	α_{SY}	α_{DHS}
WML^{FF}	0.65	0.86	0.97	0.69	-0.01	0.18	-0.00	-0.08	-0.08
t	(4.82)	(7.68)	(8.23)	(3.39)	(-1.42)	(0.77)	(-0.55)	(-0.51)	(-0.42)
$rHTP^{FF}$	0.70	0.52	0.55	0.65	0.30	0.43	0.34	0.32	0.35
t	(6.08)	(4.78)	(5.74)	(4.87)	(3.08)	(2.51)	(3.04)	(2.63)	(2.69)
$rPTH^{FF}$	0.35	0.81	0.93	0.59	0.07	0.17	0.04	-0.12	-0.28
t	(2.10)	(6.98)	(8.77)	(3.40)	(0.85)	(0.90)	(0.44)	(-0.79)	(-1.55)

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