

# Decomposing Momentum: Eliminating its Crash Component

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

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

**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 momentum stocks and short in the lowest decile yields an average monthly return of 1.18% per month over a time period from 1927 to 2020. At the same time, research has shown that momentum strategies exhibit rare but severe crashes (Daniel and Moskowitz, 2016). Indeed, momentum is highly left-skewed and fat-tailed. The strategy's worst monthly return is -77.56%. Momentum tends to crash when the market rebounds after a severe market downturn. In these situations, the market risk exposure of the long-short momentum strategy is strongly negative, implying low returns in form of crashes when the market rises. 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 paper, we show that a simple decomposition of momentum allows to avoid these crashes. More specifically, we empirically decompose momentum (*MOM*) into the two components 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, i.e., a crash-free alternative to the standard momentum strategy. Our decomposition approach simply relies on the highest stock price  $P_{high}$  during the conventional momentum formation period over months  $t - 12$  to  $t - 2$ . Utilizing  $P_{high}$ , *HTP* is the log ratio of high price to 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):

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

where  $P_0$  and  $P_1$  denote the stock price at the beginning ( $t - 12$ ) and the end ( $t - 2$ ) of the momentum formation period, respectively. Previous research has extensively documented the positive cross-sectional relationship between *MOM* and subsequent returns. Moreover, *PTH* – conceptually similar to the 52-week high measure of George and Hwang (2004) – has been shown to predict subsequent returns and to partly explain momentum profits. However, to the best of our knowledge, the remaining component *HTP* has not yet been investigated – although a corresponding long-short strategy yields 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. The corresponding long-short returns are severely left-skewed and responsible for the well-documented momentum crashes (Daniel and Moskowitz, 2016). We find that the *PTH*-strategy suffers from even worse crashes than traditional momentum. Both *MOM*- and *PTH*-strategy strongly depend on market conditions as they yield positive return spreads only in up market states (Cooper et al., 2004; Barroso and Wang, 2021) and in times of low cross-sectional return dispersion (Stivers and Sun, 2010). Following market downturns, the *PTH*-strategy's short leg – by construction – contains the most severe recent loser stocks. When the market rebounds from these bear markets, the loser stocks sharply increase in value, leading to a negative market risk exposure and crashes of the *PTH*-strategy.

Upon removing this crash-prone *PTH*-component from momentum, the remaining component *HTP* yields a monthly return premium of 1.21% 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. This results in substantially higher buy-and-hold returns for the *HTP*-strategy compared to *MOM*- and *PTH*-strategy. Moreover, *HTP* induces significantly positive return spreads in both up and down market states (Cooper et al., 2004) as well as in both times of high and low cross-sectional return dispersion (Stivers and Sun, 2010). As the *HTP*-strategy's short leg largely avoids recent loser stocks, it neither shows a negative market risk exposure nor crashes when these loser stocks recover after severe market drawdowns.

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

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

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

Second, 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.

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

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

for momentum profits to arise – the momentum component *HTP* generates significantly positive returns irrespective of these market states.

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

## 2. DATA AND VARIABLES

Our stock market analyses are mainly based on return data obtained from the Center for Research in Security Prices (CRSP). Risk-free rate and Fama and French (1993) three factor data is obtained from Kenneth R. French's homepage.<sup>1</sup> Accounting data is retrieved from COMPUSTAT. In line with Fama and French (1993), we use annual balance sheet data at the earliest at the end of June of the following year.<sup>2</sup>

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

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<sup>1</sup>See [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

<sup>2</sup>CRSP and COMPUSTAT data were provided by Wharton Research Data Services.

end of the momentum formation period. Prices are adjusted for stock splits and dividend payments before identifying  $P_{high}$ . Hence, these definitions imply  $MOM = HTP + PTH$ .

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

Our sample contains all common ordinary US stocks traded on NYSE, AMEX, or NASDAQ. The sample period for the long-short returns covers January 1927 to December 2020 since CRSP data is available since January 1926 and we need twelve months of return data to calculate the main stock-level variables. Any stock-month-observation is included in our sample if these main variables of interest  $MOM$ ,  $HTP$ , and  $PTH$  can be calculated, i.e., if stock return data for the previous twelve months is available. This leads to a total of 3,243,989 stock-month-observations.

### 3. EVIDENCE ON MOMENTUM CRASHES

#### 3.1. Long-Short Returns of the two Momentum Components

We allocate stocks to ten decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  to obtain the respective long-short portfolio returns  $WML$ ,  $rHTP$ , and

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<sup>3</sup>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 Tables A8 to A10 and Figures A2 to A5 in the Online Appendix.

<sup>4</sup>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>.



$rPTH$  in month  $t$ . Table 1 reports summary statistics for the traditional winner-minus-loser strategy  $WML$  and for the long-short strategies  $rHTP$  and  $rPTH$ .<sup>5</sup> We document a significant momentum effect of 1.18% per month. Both  $HTP$  and  $PTH$  yield significant return spreads, too, i.e., both momentum components contribute to the overall momentum phenomenon. However, the average return spread associated with  $HTP$  is 1.21% but only 0.48% for  $PTH$ . While the positive relationship between  $PTH$  and subsequent returns is qualitatively in line with George and Hwang (2004), the complementing component  $HTP$  shows substantially stronger return predictability. This observation indicates that  $PTH$  indeed contributes to momentum profits, but that large parts stem from  $HTP$  which has not received any research attention so far.

Turning to the volatility of the long-short strategies,  $rPTH$  shows the highest standard deviation resulting in a comparably low Sharpe ratio of 0.19. 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 shed more light on this, we further report the maximum drawdown of the three strategies. It is defined as the lowest hypothetical return that an investor could have achieved with the respective investment strategy. While we confirm previous literature on severe momentum crashes (maximum  $WML$  drawdown of -95.35%), 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

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

monthly returns of the three long-short strategies. The minimum of  $rPTH$  is the lowest (-83.40%), closely followed by the minimum of  $WML$  (-77.56%), while the minimum of  $rHTP$  is much smaller in absolute terms (-32.80%). These observations directly relate to the extensive research on momentum crashes (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015). We show that a strategy on the momentum component  $PTH$  implies even more negatively skewed returns than standard momentum and higher crash risk. At the same time, upon removing  $PTH$  from  $MOM$ , the resulting  $HTP$ -strategy yields long-short returns with slightly positive skewness and substantially reduced crash risk.

**Table 1. Monthly Long-Short Returns  $WML$ ,  $rHTP$ , and  $rPTH$**

This table displays summary statistics for the monthly long-short portfolio returns  $WML$ ,  $rHTP$ , and  $rPTH$ . For each month  $t$ , the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  using NYSE-breakpoints.  $MOM$  is the stock's log return over formation months  $t - 12$  to  $t - 2$ .  $HTP$  refers to the return component of  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	q0.25	q0.5	q0.75	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

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 on  $rHTP$  in January 1927 resulted in \$117,202.00 at the end of 2020 while a corresponding  $WML$ -strategy resulted in \$8,457.54 only. At first sight, it might be surprising that the cumulative return of the  $HTP$ -strategy is that much higher compared to the  $WML$ -strategy

even though their mean monthly returns are similar (see Table 1). The reason is that  $rHTP$  does not crash severely such that its geometric mean is substantially higher compared to  $WML$ . This observation underlines how strongly  $WML$  is affected by crashes while  $rHTP$  is not. With respect to  $rPTH$ , crashes have an even more severe impact on its cumulative strategy performance: a \$1 investment on  $rPTH$  in 1927 results in only \$0.52 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 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: Table A2 shows that the average monthly long-short returns  $WML$  and  $rPTH$  are indeed insignificant from July 1997 to December 2020. On the contrary,  $rHTP$  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, Online Appendix Table A2 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.<sup>6</sup>

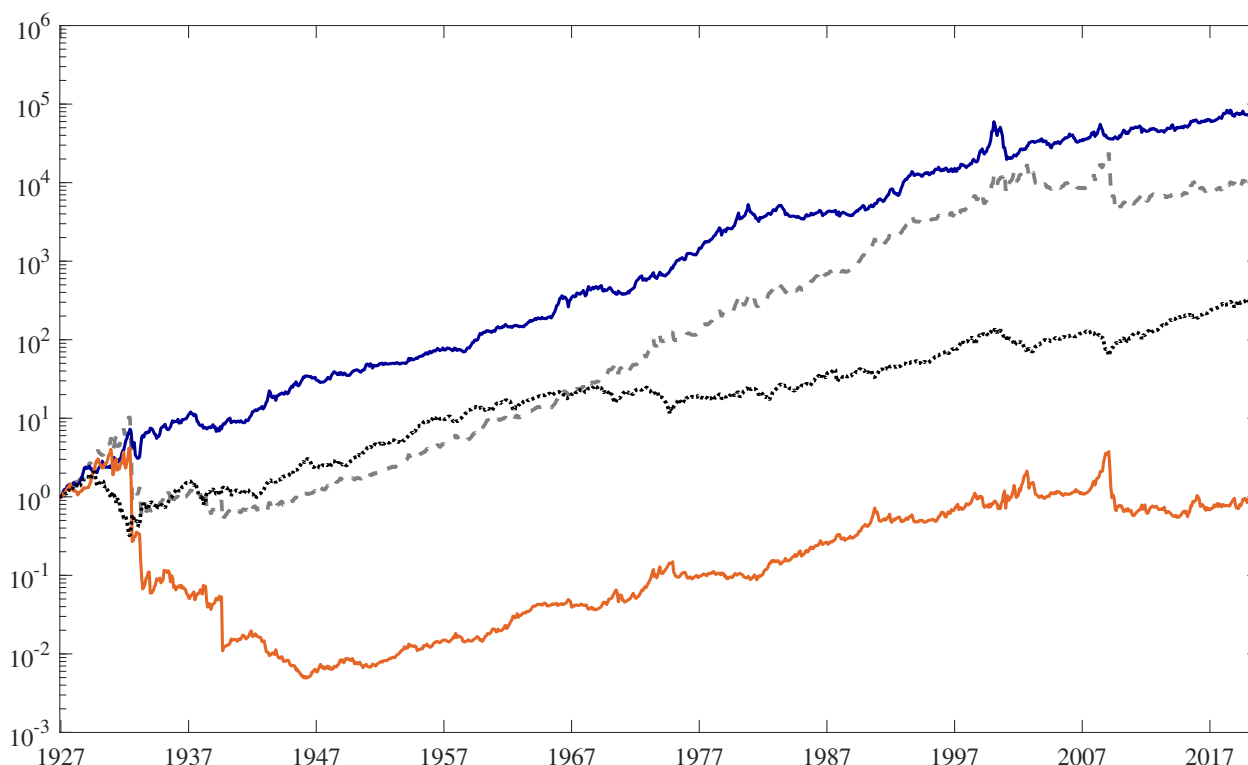
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<sup>6</sup>Figure 1 shows a strong detrimental impact of the 1930s on  $WML$  and  $rPTH$ . Note however, that our main findings in Table 1 are not merely driven by this decade: an analysis of monthly long-short returns based on

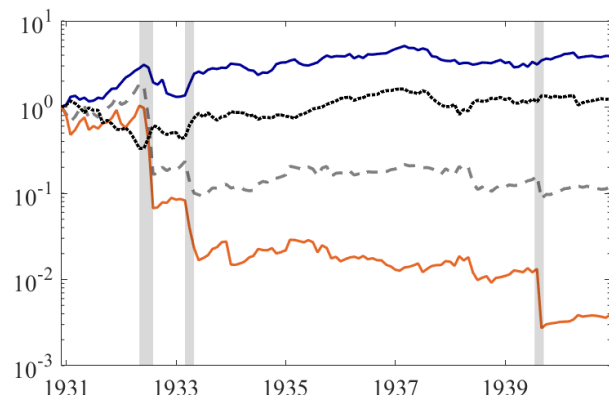
**Figure 1. Cumulative Long-Short Returns**

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

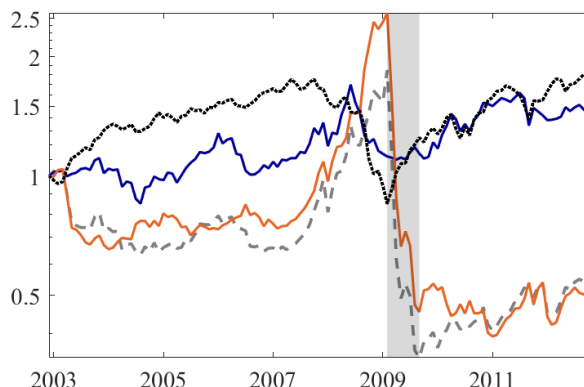
**Panel A: January 1927 to December 2020**



**Panel B: January 1931 to December 1940**



**Panel C: January 2003 to December 2012**



---  $WML$     —  $rHTP$     —  $rPTH$     .....  $MKT$

In the following, we will examine the strategies' crash properties in greater detail. To do so, we identify two major momentum crash periods, the first in the 1930s during the Great Depression and another one following the market downturn of the financial crisis in 2009. To get a better understanding of the exact movements of  $WML$ ,  $rHTP$ , and  $rPTH$  during these periods, Panels B and C from Figure 1 depict the cumulative returns during the subperiods 1931 to 1940 and 2003 to 2012 in greater detail. The two subplots demonstrate that  $WML$  and  $rPTH$  crash simultaneously whereas  $rPTH$  crashes even more severely compared to  $WML$ .<sup>7</sup> Moreover, these crashes tend to occur after market downturns when the market rebounds. On the contrary,  $rHTP$  shows a rather smooth progress over time and no signs of concomitant crashes. These much higher cumulative returns during the major crash periods play a large role in its overall better cumulative performance compared to  $WML$  and  $rPTH$ .

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

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the frequently applied more recent sample period beginning in July 1963 (George and Hwang, 2004) reveals very similar figures (see Table A3 in the Online Appendix).

<sup>7</sup>We highlight the momentum crashes by grey bars in Panels B and C for illustrative reasons and will also show these bars in the following graphs for easier orientation.

(2019), and Hoberg et al. (2020) eliminate specific subgroups of stocks from the construction of momentum portfolios in order to reduce crash risk. On the contrary, our approach avoids momentum crashes without requiring time-varying investment exposure while using the full cross-section of stocks. Instead, we propose a simple cross-sectional strategy based on the momentum component  $HTP$  which allows to completely avoid negative return skewness. Hence, crashes are no inherent property of momentum strategies but can be avoided by simply eliminating the  $PTH$ -component. This observation also shows that average momentum returns cannot be completely explained as a risk premium that compensates investors for the infrequent momentum crashes: although  $rHTP$  does not crash, it carries a significant return premium.

**Table 2. Most Extreme Momentum Crash Months**

This table shows monthly long-short portfolio returns  $WML$ ,  $rHTP$ , and  $rPTH$  for those ten months  $t$  in the sample period that show the most negative return  $WML$ . For each month  $t$ , the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  using NYSE-breakpoints.  $MOM$  is the stock's log return over formation months  $t - 12$  to  $t - 2$ .  $HTP$  refers to the return component of  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . In addition, the table shows the market excess return of month  $t$  ( $MKT$ ) as well as the cumulative market excess return of months  $t - 24$  to  $t - 1$  ( $MKT_{24m}$ ). The sample period covers January 1927 to December 2020.

month	$WML$	$rHTP$	$rPTH$	$MKT$	$MKT_{24m}$
1932, August	-77.56	-32.80	-83.40	37.06	-68.46
1932, July	-58.25	-7.15	-58.53	33.84	-75.47
1939, September	-45.93	11.27	-79.48	16.88	-21.62
2009, April	-45.10	-1.14	-44.22	10.18	-43.51
2001, January	-41.81	-14.34	-39.56	3.13	-0.28
1933, April	-41.21	35.36	-51.91	38.85	-59.65
2009, March	-39.21	-0.81	-39.01	8.95	-47.79
1938, June	-32.49	-4.55	-33.15	23.87	-28.23
1931, June	-29.44	-9.24	-28.16	13.90	-50.52
2020, April	-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 millenium 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.

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

### 3.2. Market State Dependence

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

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

Closely related to the market state is the cross-sectional dispersion in stock returns ( $RetDisp$ ) as it is a strong countercyclical indicator (Loungani et al., 1990; Gomes et al., 2003; Stivers, 2003; Zhang, 2005; and Stivers and Sun, 2010). Stivers and Sun (2010) show that momentum profitability negatively depends on cross-sectional return dispersion. We examine whether this  $WML$  property is shared by  $rHTP$  and  $rPTH$  and present the respective average long-short returns during periods of low and high cross-sectional return dispersion in Table 3. The calculation of cross-sectional return dispersion follows Stivers and Sun (2010) and we split the sample in high and low dispersion months using the median dispersion level in our sample period. Indeed,  $rPTH$  is only positive when return dispersion is low – qualitatively in line with the findings on  $WML$ . The difference between periods of low and high return dispersion is significant for both  $rPTH$  and  $WML$ . On the



**Table 3. Subperiod Analyses of Long-Short Returns  $WML$ ,  $rHTP$ , and  $rPTH$** 

This table shows average monthly long-short portfolio returns  $WML$ ,  $rHTP$ , and  $rPTH$  for different market state and return dispersion subperiods. For each month  $t$ , the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  using NYSE-breakpoints.  $MOM$  is the stock's log return over formation months  $t - 12$  to  $t - 2$ .  $HTP$  refers to the return component of  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . Following Cooper et al. (2004), the up (down) market state subperiod includes all months  $t$  for which the market return over months  $t - 36$  to  $t - 1$  is positive (negative). Following Stivers and Sun (2010), for each month, return dispersion is measured as the cross-sectional return standard deviation of 100 size/book-to-market portfolios (obtained from Kenneth R. French's homepage). Each month  $t$  is considered as high (low) return dispersion month if the average return dispersion of months  $t - 3$  to  $t - 1$  is above (below) the time-series median. The t-statistics in parentheses refer to the subperiod average returns of  $WML$ ,  $rHTP$ , and  $rPTH$  and are based on standard errors following Newey and West (1987) using twelve lags.  $\Delta$  refers to the difference between the two respective subperiods. The corresponding t-statistics are based on two-sample t-tests (Welch's t-test with unequal variances). The sample period covers January 1927 to December 2020.

	$WML$				$rHTP$				$rPTH$			
	MktState		RetDisp		MktState		RetDisp		MktState		RetDisp	
	Up	Down	Low	High	Up	Down	Low	High	Up	Down	Low	High
mean	1.41	-0.50	1.73	0.63	1.06	1.70	1.16	1.25	0.81	-1.79	1.29	-0.34
t	(7.77)	(-0.55)	(7.82)	(1.69)	(5.54)	(3.10)	(6.02)	(4.03)	(3.88)	(-1.63)	(6.09)	(-0.75)
$\Delta$	1.90		1.10		-0.65		-0.09		2.60		1.63	
t	(2.06)		(2.53)		(-1.11)		(-0.25)		(2.33)		(3.27)	

contrary,  $rHTP$  does not depend on the level of return dispersion: it generates monthly return spreads of more than 1% in both subperiods.

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

#### 4. DRIVERS OF MOMENTUM CRASHES

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

##### 4.1. Loser Stocks

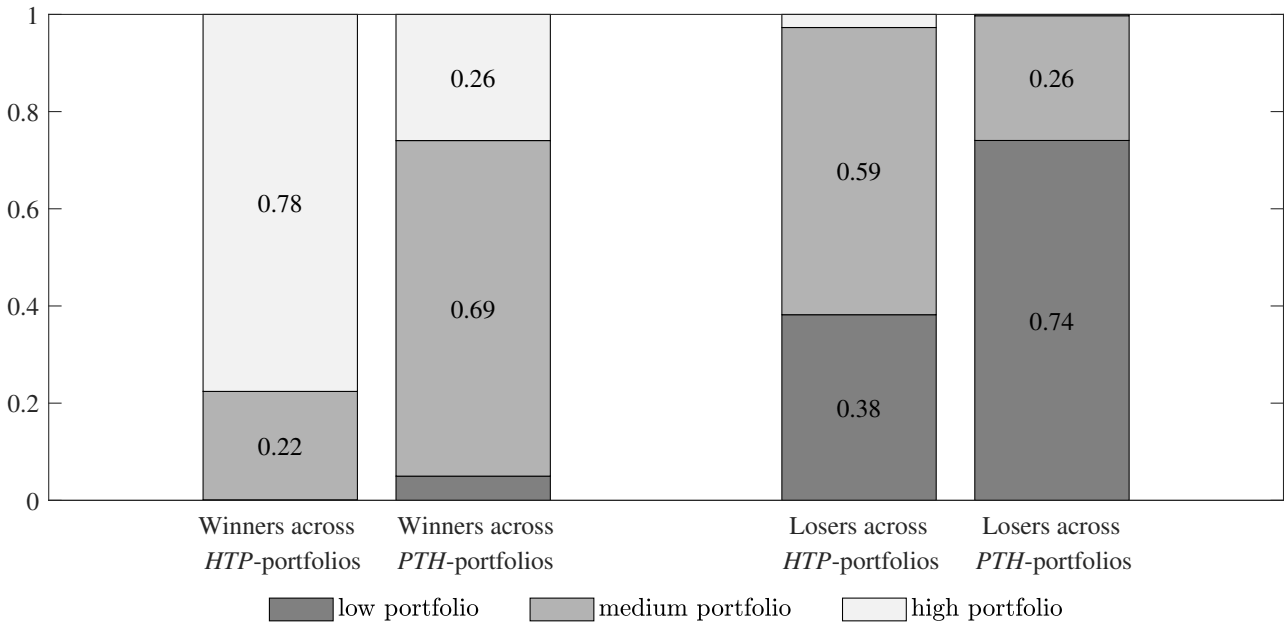
Daniel and Moskowitz (2016) show that momentum crashes are driven by the loser stocks in the bottom  $MOM$ -decile. We therefore examine to which extent winner and loser stocks

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

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

**Figure 2. Winner and Loser Stocks in Long and Short Leg of HTP- and PTH-Strategies**

The two bars on the left show the time-series average proportion of winner stocks assigned to different HTP-portfolios (PTH-portfolios). The two bars on the right show the time-series average proportion of loser stocks assigned to different HTP-portfolios (PTH-portfolios). For each month  $t$ , winner (loser) stocks are identified as the stocks in the highest (lowest) MOM-decile. The bars show the proportion of these stocks that are simultaneously identified as low- (bottom decile), medium- (deciles two to nine), or high- (top decile) HTP (PTH). MOM is the stock's log return over formation months  $t - 12$  to  $t - 2$ . HTP refers to the return component of MOM which is realized before the formation period's highest stock price  $P_{high}$ . PTH refers to the return component of MOM which is realized after the formation period's highest stock price  $P_{high}$ . The sample period covers January 1927 to December 2020.



As expected, both  $r_{HTP}$  and  $r_{PTH}$  show a significantly positive correlation with  $WML$  as the underlying variables  $HTP$ ,  $PTH$ , and  $MOM$  are linearly related by construction. Notably, the correlation between  $r_{PTH}$  and  $WML$  is considerably higher than that of  $r_{HTP}$  and  $WML$ . This is consistent with the graphical evidence in Figure 1 which illustrates that  $WML$  and  $r_{PTH}$  crash simultaneously.<sup>8</sup> Further, the correlation between  $WML_{LL}$  and  $r_{HTP}$  is 69% while the correlation between  $WML_{LL}$  and  $r_{PTH}$  is only 34%. This observation is in line with the evidence from Figure 2 that winner stocks (which contribute

<sup>8</sup>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  $WML$ - $r_{PTH}$ -correlation already drops to 0.68 while the  $WML$ - $r_{HTP}$ -correlation increases to 0.45 (see Table A6 in the Online Appendix).

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

**Table 4. Correlation of  $WML$ ,  $WML_{LL}$ ,  $WML_{SL}$ ,  $rHTP$ , and  $rPTH$**

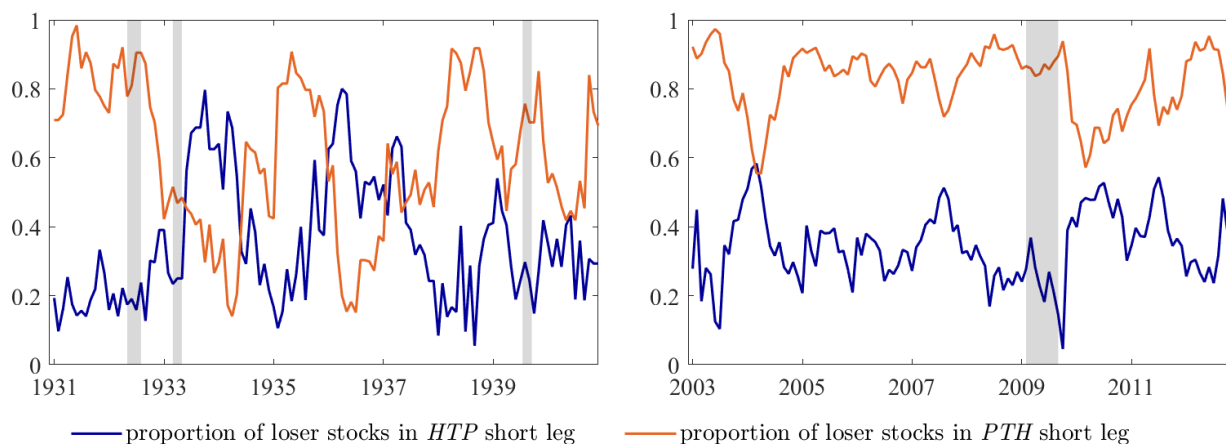
This table displays the return correlation coefficients for monthly  $WML$ , long leg-based  $WML$ , short leg-based  $WML$ ,  $rHTP$ , and  $rPTH$ . For each month  $t$ ,  $WML$  is the value-weighted return difference between top- and bottom- $MOM$  decile.  $WML_{LL}$  is the value-weighted return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

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

**Figure 3. Loser Stocks in Short Leg of *HTP*- and *PTH*-Strategies**

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



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

#### 4.2. Time Varying Market Betas and Optionality

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

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

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

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

Regression specification (1) in Table 5 shows that all three strategies *WML*, *rHTP*, and *rPTH* yield significant return premiums after accounting for market risk. The negative market beta of *WML* is in line with Daniel and Moskowitz (2016). Moreover, the long-short strategy based on *HTP* has a positive market beta of 0.34 (t=3.40) while the long-short strategy based on *PTH* has a negative market beta of -1.02 (t=-9.52). These differences can be rationalized by the construction of *HTP* and *PTH*. Stocks with a high market beta tend to outperform during up markets. As *HTP* measures the strength of a stock's up movement that leads to  $P_{high}$ , high-*HTP* stocks have higher market betas on average. On the contrary,

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

Regression specification (2) provides two major insights. First, all three long-short strategies provide significantly positive market-adjusted returns in bull markets ( $\alpha_0$ ). However, in bear markets, the alphas of *WML* and *rPTH* decline by 1.80% ( $t=-2.67$ ) and 2.45% ( $t=-2.96$ ), respectively, and thus turn negative. In line with Table 3, only *rHTP* does not provide lower returns during bear markets. Second, the market betas of *rHTP*, *rPTH*, and *WML* are significantly lower in bear than in bull markets. However, while the *rHTP* market beta remains positive even in bear markets, *rPTH* shows a strong negative market risk exposure during bear markets (market beta of -1.43).

Turning to regression specification (3), the findings with respect to *WML* are in line with Daniel and Moskowitz (2016): the *WML* market beta is negative in bear markets and even more so when the market rebounds, i.e., when the value-weighted market excess return is positive. Hence, *WML* behaves like a written call option on the market. This interpretation also applies to *rPTH*; the negative market risk exposure is even more pronounced: during market rebounds in bear periods, *rPTH* shows a negative market beta of -1.81. Hence, the overall negative market risk exposure of *rPTH* is even more negative during bear markets and market rebounds explaining the severe *rPTH* crashes. On the contrary, the market beta of *rHTP* remains positive when the market recovers from bear markets. In none of the three regression specifications, *rHTP* exhibits a negative market beta which points out that the long-short strategy based on *HTP* does not show option-like behavior with respect to the market.

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



**Table 5. Time Varying Market Betas and Optionality of  $WML$ ,  $rHTP$ , and  $rPTH$**

This table shows regression coefficients for the time-series regression  $WML_t = \alpha_0 + \alpha_B B_t + \beta_0 MKT_t + \beta_B MKT_t B_t + \beta_{B,R} MKT_t B_t R_t + \epsilon_t$ . In alternative specifications,  $rHTP$  and  $rPTH$  are used as dependent variables instead of  $WML$ . For each month  $t$ , the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  using NYSE-breakpoints.  $MKT_t$  is the excess market return in month  $t$ .  $B_t$  is a bear market dummy which equals one if the market return over months  $t - 24$  to  $t - 1$  is negative and zero otherwise.  $R_t$  is a rebound dummy which equals one if the excess market return in month  $t$  is positive and zero otherwise. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers January 1927 to December 2020.

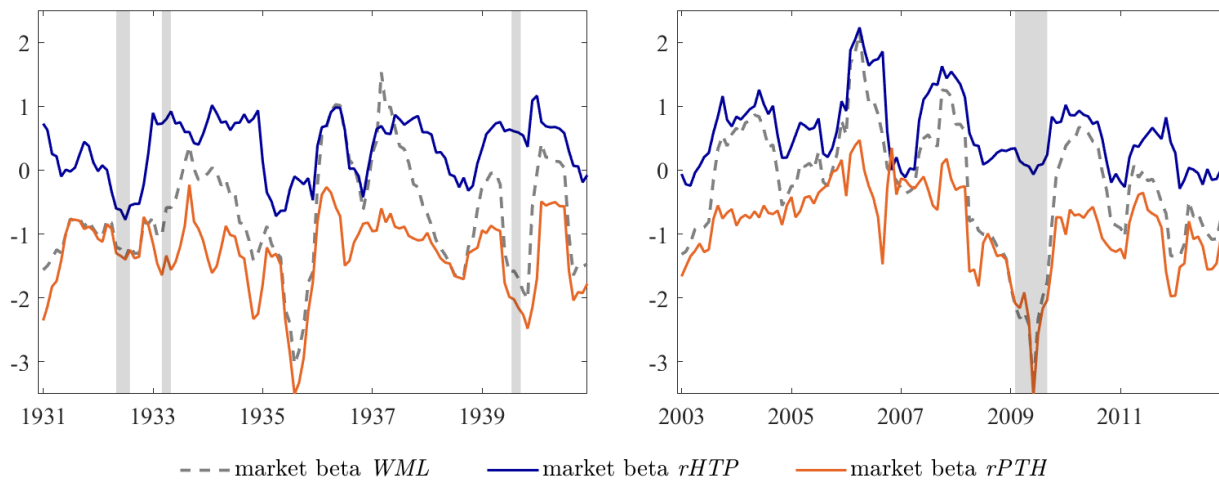
	$WML$			$rHTP$			$rPTH$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\alpha_0$	1.56	1.59	1.59	0.97	0.75	0.75	1.17	1.39	1.39
t	(8.81)	(8.84)	(8.84)	(5.04)	(4.05)	(4.05)	(6.31)	(7.90)	(7.89)
$\alpha_B$		-1.80	0.62		0.67	0.41		-2.45	0.55
t		(-2.67)	(0.70)		(1.19)	(0.35)		(-2.96)	(0.68)
$\beta_0$	-0.55	-0.07	-0.07	0.34	0.53	0.53	-1.02	-0.69	-0.69
t	(-3.67)	(-0.95)	(-0.95)	(3.40)	(8.24)	(8.24)	(-9.52)	(-9.87)	(-9.87)
$\beta_B$		-1.06	-0.61		-0.40	-0.45		-0.74	-0.19
t		(-6.77)	(-4.42)		(-2.21)	(-3.42)		(-5.48)	(-1.56)
$\beta_{B,R}$			-0.75			0.08			-0.93
t			(-3.29)			(0.22)			(-4.63)

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

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

**Figure 4. Rolling Market Betas of  $WML$ ,  $rHTP$ , and  $rPTH$** 

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



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

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

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

## 5. CROSS-SECTIONAL ANALYSIS OF $MOM$ , $HTP$ , AND $PTH$

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

$$\hat{\gamma}_{MOM} = \frac{\sigma_{HTP}^2}{\sigma_{MOM}^2} \hat{\gamma}_{HTP} + \frac{\sigma_{PTH}^2}{\sigma_{MOM}^2} \hat{\gamma}_{PTH} \quad (3)$$

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

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

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

To investigate the relationship between *MOM*, *HTP*, *PTH*, and subsequent returns, we first run cross-sectional regressions following Fama and MacBeth (1973). The regression analyses also allow us to test whether the return predictability associated with *MOM*, *HTP*, and *PTH* is subsumed by standard control variables. Regression specifications (1) to (3) in Table 6 show that *MOM* as well as both *HTP* and *PTH* positively predict one-month-ahead stock returns with high statistical significance. The return predictability of *HTP* and *PTH* remains significant when we control for a 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*). Noteworthy, the coefficient magnitude of *HTP* is slightly higher than that of *PTH* in regression specification (4), but is slightly lower in regression specifications (5) and (6) when adding control variables. Hence, neither *HTP* nor *PTH* can be considered as the clearly dominant component with respect to explaining momentum profits.<sup>9</sup> This observation thus reinforces our argument

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<sup>9</sup>Note that these regression analyses indicate similar return predictive power for *HTP* and *PTH* whereas the mean of  $rPTH$  is considerably higher than the mean of  $rHTP$  (see Table 1). The reason is that the Fama-MacBeth-regressions in Table 6 apply *equal*-weighted OLS regressions while  $rPTH$  and  $rHTP$  are based on *value*-weighted portfolios. Table A7 in the Online Appendix presents value-weighted Fama-MacBeth-regressions: the resulting regression coefficients are consistently larger for *HTP* compared to *PTH*.

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

**Table 6. MOM, HTP, and PTH in Fama-MacBeth-Regressions**

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

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

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

Novy-Marx (2012) also decomposes the total momentum formation period (months  $t - 12$  to  $t - 2$ ) and shows that momentum profits largely stem from months  $t - 12$  to  $t - 7$ . *IMOM* might thus be closely related to *HTP* which also measures a stock's return over the beginning of the momentum formation period. However, while Novy-Marx (2012) uses a fixed point in time to split up *MOM*, our decomposition approach is dynamic in the sense that it depends on the timing of  $P_{high}$ . Table 6 shows that the return predictability of *HTP* and *PTH* is not captured by the intermediate momentum return *IMOM*.<sup>10</sup> It is even the other way round: in untabulated regressions, we find that *IMOM* is a significantly positive return predictor if we drop *HTP* as explanatory variable. But with *HTP*, Table 6 shows that the *IMOM*-coefficient is insignificant. As additional robustness check, Table A4 in the Online Appendix examines long-short returns based on *IMOM*, complementary to Table 1. While *IMOM* is a significant return predictor, the corresponding return spread is slightly smaller compared to *HTP*. More importantly, the *IMOM*-based long-short strategy yields negatively skewed returns and is prone to severe crash risk (e.g., minimum monthly return of -90.66% compared to -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.

## 5.2. Contribution of *HTP* and *PTH* to Momentum Effect

The regressions in the previous subsection suggest that *HTP* and *PTH* contribute to the overall momentum effect to a similar extent. In addition, Section 3 provides evidence that the long-short returns associated with *PTH* are prone to severe crashes while those associated

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<sup>10</sup>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.

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

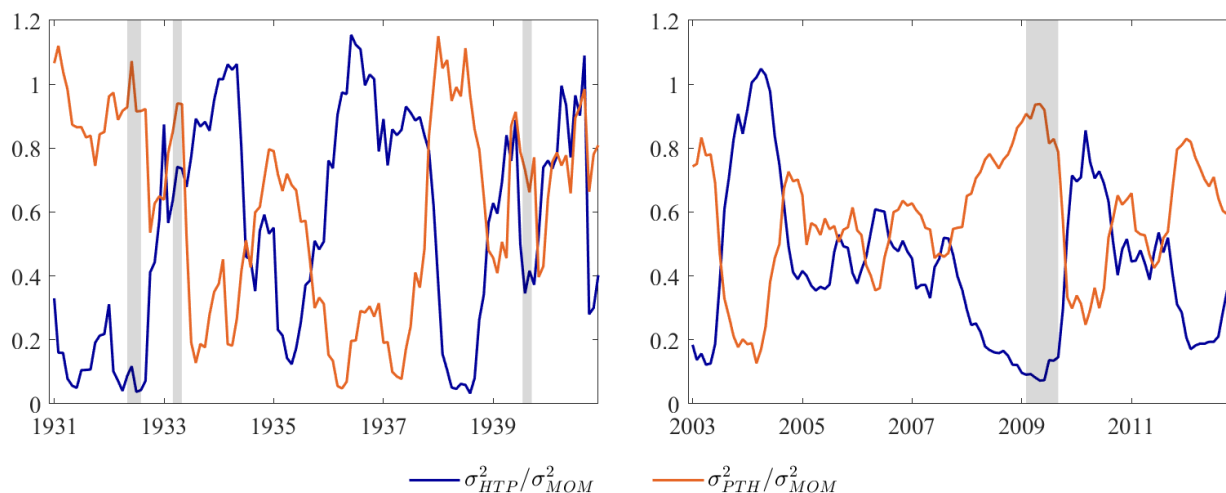
The high value of  $\sigma_{PTH}^2/\sigma_{MOM}^2$  during crash periods can be traced back to two sources. First, as the crash periods follow market downturns, a comparably large proportion of the momentum formation period belongs to  $PTH$  rather than  $HTP$  as the former measures a stock's price decline following  $P_{high}$ .<sup>11</sup> 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  $\sigma_{PTH}^2/\sigma_{MOM}^2$  when  $rPTH$  crashes such that  $WML$  crashes as well. Hence, our analyses allow to trace back momentum crashes to the  $MOM$ -component  $PTH$

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<sup>11</sup>The proportion of the  $MOM$  formation period which is covered by  $HTP$  versus  $PTH$  is plotted in Figure A1 in the Online Appendix: during crash months, the formation period proportion covered by  $PTH$  is higher than the proportion covered by  $HTP$ .

**Figure 5. HTP- and PTH-Weights for the Momentum Effect**

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



rather than *HTP*. Vice versa, the elimination of *PTH* from *MOM* allows to substantially reduce crash risk.

## 6. CONCLUSION

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



return and an even higher Sharpe ratio. These findings challenge existing theories for the profitability of momentum that rely on momentum's crash property or its market state dependence. Hence, while economic mechanisms related to the *PTH*-component have been extensively studied in the 52-week high literature, the driving forces of the *HTP*-induced return predictability require further investigation.

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**Online Appendix for**

**"Decomposing Momentum: Eliminating its Crash Component"**

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Susanne Siedhoff<sup>§</sup>

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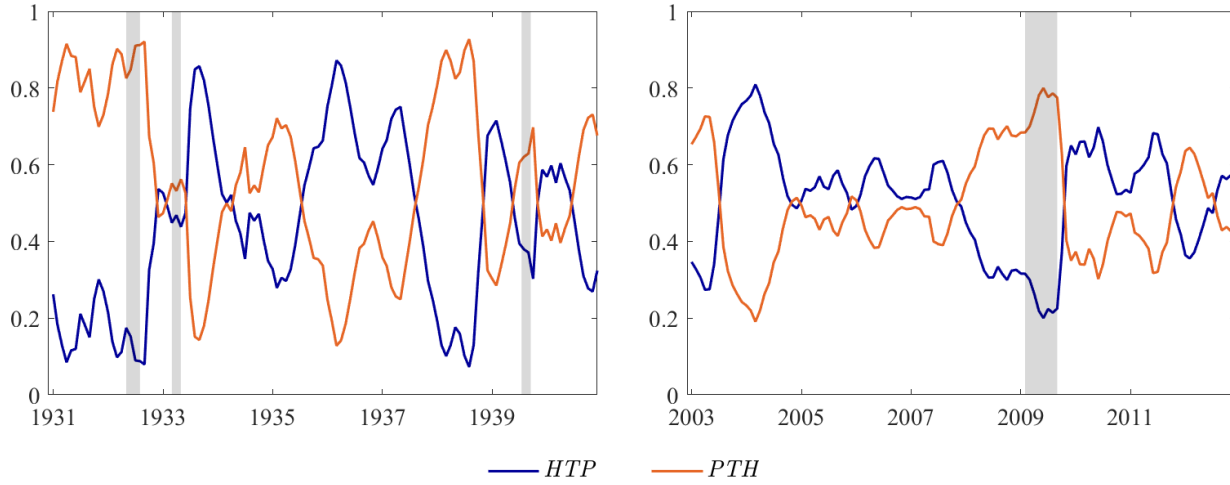
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**Figure A1. Proportion of Momentum Formation Period Covered by *HTP* and *PTH***

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.



## Decomposing Momentum: Eliminating its Crash Component

**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* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . At the end of each month, each stock is allocated to one decile portfolio based on *MOM*, *HTP*, or *PTH*. Portfolio sorts are based on NYSE-breakpoints. For the subsequent month  $t$ , this table presents raw returns as well as portfolio alphas accounting for the three Fama and French (1993) factors. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The sample period covers January 1927 to December 2020.

	<i>MOM</i>				<i>HTP</i>				<i>PTH</i>			
	value		equal		value		equal		value		equal	
	raw	$\alpha$	raw	$\alpha$	raw	$\alpha$	raw	$\alpha$	raw	$\alpha$	raw	$\alpha$
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)



## Decomposing Momentum: Eliminating its Crash Component

**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  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 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 <sub>0.25</sub>	q <sub>0.5</sub>	q <sub>0.75</sub>	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 <sub>0.25</sub>	q <sub>0.5</sub>	q <sub>0.75</sub>	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 <sub>0.25</sub>	q <sub>0.5</sub>	q <sub>0.75</sub>	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 <sub>0.25</sub>	q <sub>0.5</sub>	q <sub>0.75</sub>	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  $rPTH$  from July 1963 to December 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  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers July 1963 to December 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	q <sub>0.25</sub>	q <sub>0.5</sub>	q <sub>0.75</sub>	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	q0.25	q0.5	q0.75	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 Subperiod Analysis of Long-Short Returns  $WML$ ,  $rHTP$ , and  $rPTH$**

This table shows average monthly long-short portfolio returns  $WML$ ,  $rHTP$ , and  $rPTH$  for different volatility states. For each month  $t$ , the long-short returns are calculated as the difference between top and bottom decile value-weighted portfolio returns. Stocks are allocated to these decile portfolios based on  $MOM$ ,  $HTP$ , and  $PTH$  at the end of each month  $t - 1$  using NYSE-breakpoints.  $MOM$  is the stock's log return over formation months  $t - 12$  to  $t - 2$ .  $HTP$  refers to the return component of  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . Following Barroso and Wang (2021), high (low) volatility months are months in which the volatility of long-short portfolio returns  $WML$ ,  $rHTP$ , and  $rPTH$ , is above (below) the 70%- (30%-) time-series percentile of volatilities, respectively.  $WML-$ ,  $rHTP-$ , and  $rPTH-$  volatilities are based on long-short portfolio returns over the previous 126 trading days as in Barroso and Santa-Clara (2015). 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.  $\Delta$  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 January 1927 to December 2020.

Volatility	$WML$		$rHTP$		$rPTH$	
	Low	High	Low	High	Low	High
mean	2.12	0.16	1.07	0.96	1.17	-0.50
t	(10.54)	(0.26)	(5.50)	(1.93)	(5.44)	(-0.68)
$\Delta$	1.96		0.11		1.66	
t	(3.00)		(0.20)		(2.18)	

## Decomposing Momentum: Eliminating its Crash Component

**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  $MOM$  which is realized before the formation period's highest stock price  $P_{high}$ .  $PTH$  refers to the return component of  $MOM$  which is realized after the formation period's highest stock price  $P_{high}$ . The t-statistics for correlation coefficients are shown in the right part of the table. The sample period covers January 1927 to December 2020. We exclude the ten most extreme momentum crash months considered in Table 2 here.

	Correlation Coefficient					t-statistics				
	$WML$	$WML_{LL}$	$WML_{SL}$	$rHTP$	$rPTH$	$WML$	$WML_{LL}$	$WML_{SL}$	$rHTP$	$rPTH$
$WML$	1.00									
$WML_{LL}$	0.71	1.00				33.48				
$WML_{SL}$	0.81	0.16	1.00			45.76	5.25			
$rHTP$	0.45	0.76	0.00	1.00		16.98	38.87	0.02		
$rPTH$	0.68	0.15	0.83	-0.16	1.00	30.94	4.99	49.15	-5.40	

**Table A7. MOM, HTP, and PTH in Value-Weighted Fama-MacBeth-Regressions**

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

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

**Table A8. Monthly Long-Short Returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$**

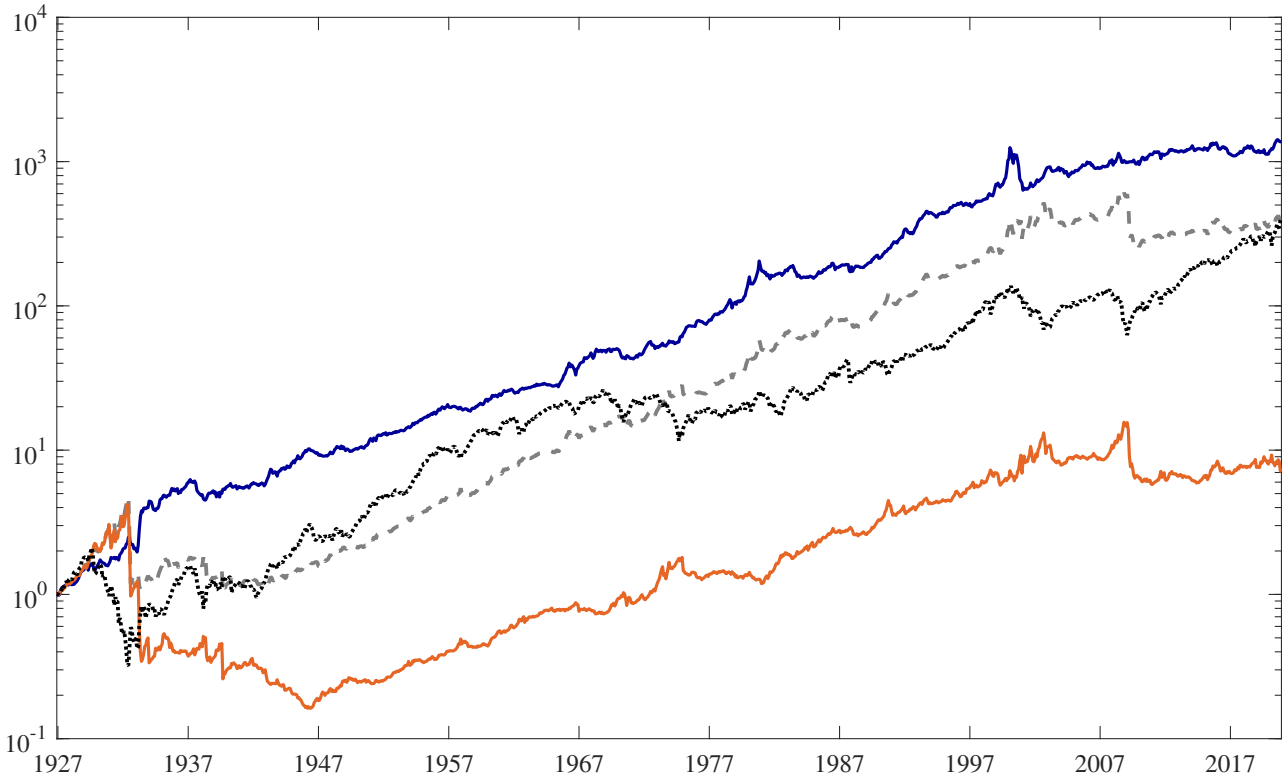
This table displays summary statistics for monthly  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$ . We construct the long-short returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  according to the *UMD* momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on *MOM*, *HTP*, or *PTH* and two size portfolios. Each month, the *MOM*, *HTP*, and *PTH* breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity.  $WML^{FF}$  ( $rHTP^{FF}$ ,  $rPTH^{FF}$ ) is defined as the mean return of the two high-*MOM* (*HTP*, *PTH*) portfolios minus the mean return of the two low-*MOM* (*HTP*, *PTH*) portfolios. *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . The summary statistics include mean, the t-statistic of the mean based on Newey and West (1987) standard errors using twelve lags, standard deviation, annualized Sharpe ratio, skewness, kurtosis, maximum drawdown, minimum, 25%-, 50%-, 75%-quantile, and maximum. The sample period covers January 1927 to December 2020.

	mean	t(mean)	std	SR	skew	kurt	maxDD	min	q0.25	q0.5	q0.75	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

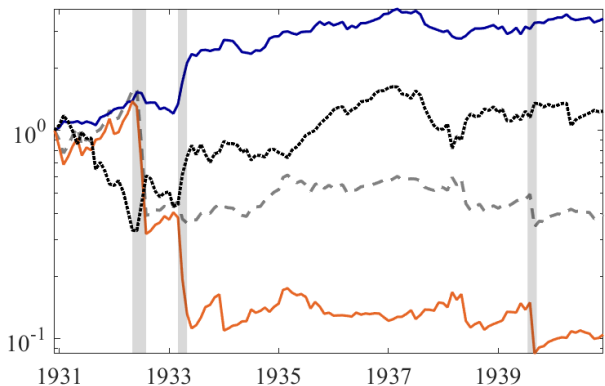
**Figure A2. Cumulative Long-Short Returns**

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*.

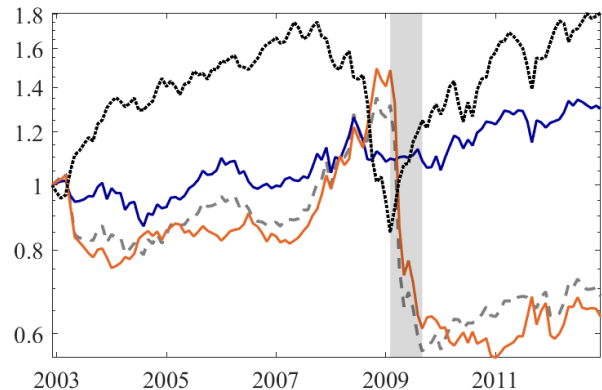
**Panel A: January 1927 to December 2020**



**Panel B: January 1931 to December 1940**



**Panel C: January 2003 to December 2012**



---  $WML^{FF}$     —  $rHTP^{FF}$     —  $rPTH^{FF}$     ..... *MKT*



**Table A9. Most Extreme Momentum Crash Months**

This table shows  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  for those ten months  $t$  in the sample period that show the most negative return  $WML^{FF}$ . We construct the long-short returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  according to the *UMD* momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on *MOM*, *HTP*, or *PTH* and two size portfolios. Each month, the *MOM*, *HTP*, and *PTH* breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity.  $WML^{FF}$  ( $rHTP^{FF}$ ,  $rPTH^{FF}$ ) is defined as the mean return of the two high-*MOM* (*HTP*, *PTH*) portfolios minus the mean return of the two low-*MOM* (*HTP*, *PTH*) portfolios. *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . In addition, the table shows the market excess return of month  $t$  (*MKT*) as well as the cumulative market excess return of months  $t - 24$  to  $t - 1$  ( $MKT_{24m}$ ). The sample period covers January 1927 to December 2020.

month	$WML^{FF}$	$rHTP^{FF}$	$rPTH^{FF}$	<i>MKT</i>	$MKT_{24m}$
1932, August	-54.00	-10.42	-53.19	37.06	-68.46
1932, July	-46.22	-0.86	-47.60	33.84	-75.47
2009, April	-34.99	0.89	-34.52	10.18	-43.51
1939, September	-30.34	6.89	-43.16	16.88	-21.62
2001, January	-25.32	-3.27	-25.01	3.13	-0.28
1938, June	-23.66	3.07	-25.56	23.87	-28.23
1931, June	-18.34	-2.60	-17.20	13.90	-50.52
1933, April	-17.03	28.47	-49.75	38.85	-59.65
2002, November	-16.33	3.97	-19.42	5.96	-40.13
1975, January	-13.64	5.77	-19.02	13.66	-49.72

## Decomposing Momentum: Eliminating its Crash Component

**Table A10. Subperiod Analyses of  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$**

This table shows average monthly returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  for different market state and return dispersion subperiods. We construct the long-short returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  according to the *UMD* momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on *MOM*, *HTP*, or *PTH* and two size portfolios. Each month, the *MOM*, *HTP*, and *PTH* breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity.  $WML^{FF}$  ( $rHTP^{FF}$ ,  $rPTH^{FF}$ ) is defined as the mean return of the two high-*MOM* (*HTP*, *PTH*) portfolios minus the mean return of the two low-*MOM* (*HTP*, *PTH*) portfolios. *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . Following Cooper et al. (2004), the up (down) market state subperiod includes all months  $t$  for which the market return over months  $t - 36$  to  $t - 1$  is positive (negative). Following Stivers and Sun (2010), for each month, return dispersion is measured as the cross-sectional return standard deviation of 100 size/book-to-market portfolios (obtained from Kenneth R. French's homepage). Each month  $t$  is considered as high (low) return dispersion month if the average return dispersion of months  $t - 3$  to  $t - 1$  is above (below) the time-series median. The t-statistics in parentheses refer to the subperiod average returns of  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  and are based on standard errors following Newey and West (1987) using twelve lags.  $\Delta$  refers to the difference between the two respective subperiods. The corresponding t-statistics are based on two-sample t-tests (Welch's t-test with unequal variances). The sample period covers January 1927 to December 2020.

	$WML^{FF}$				$rHTP^{FF}$				$rPTH^{FF}$			
	MktState		RetDisp		MktState		RetDisp		MktState		RetDisp	
	Up	Down	Low	High	Up	Down	Low	High	Up	Down	Low	High
mean	0.80	-0.42	0.96	0.34	0.61	1.06	0.62	0.78	0.58	-1.17	0.87	-0.16
t	(7.34)	(-0.71)	(7.21)	(1.36)	(5.15)	(2.79)	(4.98)	(3.92)	(4.78)	(-1.55)	(6.65)	(-0.52)
$\Delta$	1.22		0.63		-0.46		-0.16		1.75		1.02	
t	(2.05)		(2.22)		(-1.15)		(-0.68)		(2.29)		(3.10)	

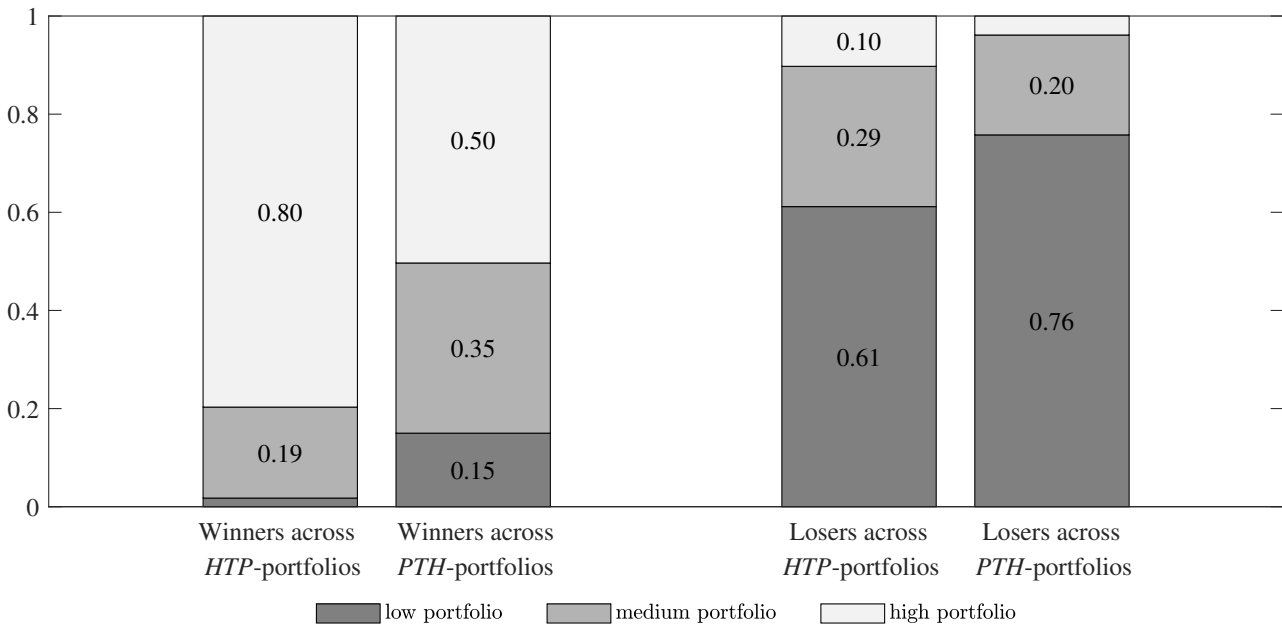
## Decomposing Momentum: Eliminating its Crash Component

**Table A11. Volatility Subperiod Analysis of Long-Short Returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$**   
This table shows average monthly returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  for different market state and return dispersion subperiods. We construct the long-short returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$  according to the *UMD* momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on *MOM*, *HTP*, or *PTH* and two size portfolios. Each month, the *MOM*, *HTP*, and *PTH* breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity.  $WML^{FF}$  ( $rHTP^{FF}$ ,  $rPTH^{FF}$ ) is defined as the mean return of the two high-*MOM* (*HTP*, *PTH*) portfolios minus the mean return of the two low-*MOM* (*HTP*, *PTH*) portfolios. *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . Following Barroso and Wang (2021), high (low) volatility months are months in which the volatility of returns  $WML^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$ , is above (below) the 70%- (30%-) time-series percentile of volatilities, respectively.  $WML^{FF-}$ ,  $rHTP^{FF-}$ , and  $rPTH^{FF-}$  volatilities are based on average returns over the previous 126 trading days as in Barroso and Santa-Clara (2015). 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.  $\Delta$  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 January 1927 to December 2020.

Volatility	<i>WML</i>		<i>rHTP</i>		<i>rPTH</i>	
	Low	High	Low	High	Low	High
mean	1.05	-0.00	0.67	0.71	0.63	-0.31
t	(9.16)	(-0.01)	(6.33)	(2.24)	(5.26)	(-0.65)
$\Delta$	1.05		-0.04		0.94	
t	(2.72)		(-0.11)		(1.91)	

**Figure A3. Winner and Loser Stocks in Long and Short Leg of *HTP*- and *PTH*-Strategies**

The two bars on the left show the time-series average proportion of winner stocks assigned to different *HTP*-portfolios (*PTH*-portfolios). The two bars on the right show the time-series average proportion of loser stocks assigned to different *HTP*-portfolios (*PTH*-portfolios). Winner and loser stocks as well as low, medium, and high *HTP*-portfolios (*PTH*-portfolios) are defined in accordance with the *UMD* momentum factor construction by Fama and French (2018), i.e., we use the intersections of three portfolios formed on *MOM*, *HTP*, or *PTH* and two size portfolios. Each month, the *MOM*, *HTP*, and *PTH* breakpoints are based on 30th and 70th NYSE percentiles; size breakpoints are given by the median NYSE market equity. The bars show the proportion of winner and loser stocks that are simultaneously identified as low-, medium-, or high-*HTP* (*PTH*). *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . The sample period covers January 1927 to December 2020.



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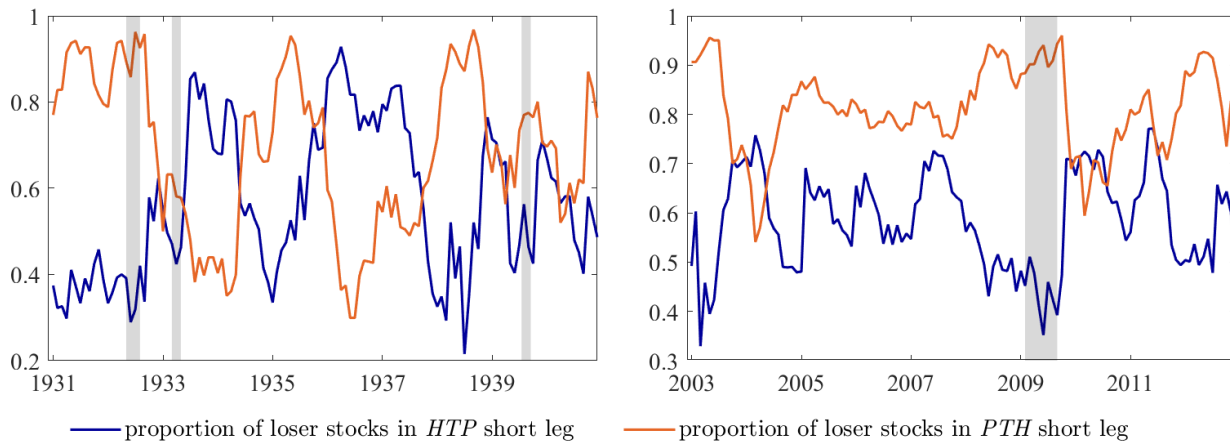
**Table A12. Correlation of  $WML^{FF}$ ,  $WML_{LL}^{FF}$ ,  $WML_{SL}^{FF}$ ,  $rHTP^{FF}$ , and  $rPTH^{FF}$**

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).  $WML_{LL}^{FF}$  is the return difference between the top 30% and medium 40% *MOM*-portfolios.  $WML_{SL}^{FF}$  is the return difference between medium 40% and bottom 30% *MOM*-portfolios.  $rHTP^{FF}$  and  $rPTH^{FF}$  are the long-short returns based on *HTP* and *PTH*, respectively, defined in accordance with the methodology of Fama and French (2018). *MOM* is the stock's log return over formation months  $t - 12$  to  $t - 2$ . *HTP* refers to the return component of *MOM* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . The t-statistics for each correlation coefficient are shown in the right part of the table. The sample period covers January 1927 to December 2020.

	Correlation Coefficient					t-statistics				
	$WML^{FF}$	$WML_{LL}^{FF}$	$WML_{SL}^{FF}$	$rHTP^{FF}$	$rPTH^{FF}$	$WML^{FF}$	$WML_{LL}^{FF}$	$WML_{SL}^{FF}$	$rHTP^{FF}$	$rPTH^{FF}$
$WML^{FF}$	1.00									
$WML_{LL}^{FF}$	0.83	1.00				49.61				
$WML_{SL}^{FF}$	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* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.



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**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 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.

	$WML^{FF}$			$rHTP^{FF}$			$rPTH^{FF}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\alpha_0$	0.86	0.87	0.87	0.52	0.39	0.39	0.81	0.91	0.91
t	(7.68)	(8.12)	(8.12)	(4.78)	(3.62)	(3.62)	(6.98)	(8.69)	(8.69)
$\alpha_B$		-1.04	0.63		0.50	-0.08		-1.53	0.93
t		(-2.35)	(0.84)		(1.52)	(-0.12)		(-3.00)	(1.77)
$\beta_0$	-0.31	0.01	0.01	0.25	0.34	0.34	-0.67	-0.43	-0.43
t	(-2.94)	(0.16)	(0.16)	(4.54)	(8.35)	(8.35)	(-7.82)	(-9.53)	(-9.53)
$\beta_B$		-0.70	-0.39		-0.19	-0.29		-0.54	-0.09
t		(-5.44)	(-4.04)		(-1.70)	(-3.85)		(-5.62)	(-1.25)
$\beta_{B,R}$			-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* which is realized before the formation period's highest stock price  $P_{high}$ . *PTH* refers to the return component of *MOM* which is realized after the formation period's highest stock price  $P_{high}$ . Market betas are based on six-month rolling windows of daily returns and take into account ten daily lags for the market return. The sample period covers January 1931 to December 1940 in the left subfigure and January 2003 to December 2012 in the right subfigure.

