Momentum Crashes: The Long & the Short of It

Momentum investing has enjoyed persistent outperformance over longer time horizons. However, a consistent pushback against momentum is the strategy's susceptibility to *crashes* – short*,* sharp periods of underperformance. We find that these regimes of underperformance are typically characterized by prior market decline and occur during the subsequent market rebound. To this point, most academic studies on momentum crashes involve drawdown analysis of a long/short portfolio formed by buying prior winners and shorting prior losers. To wit, we note that the largest momentum crashes are almost fully explained by the short side *crashing upwards* due to its rising exposure to beta in a market rebound, while the long side of the strategy faces far less dramatic drawdowns.

In addition, we find that these periods of momentum underperformance can be nearly fully abated by investing in the winners portfolio (long only momentum) combined with a long only value component.

Travis Prentice
Chief Investment Officer
Portfolio Manager

David Wroblewski
Director of Applied Research

Sample data and return distributions

All disciplined investment strategies go through periods of underperformance, and momentum investing is no different. However, understanding the anatomy of underperformance regimes can better help investors predict/hedge outcomes in their portfolio.

The standard definition of the momentum factor (WML or winners minus losers) is based on Carhart (1997) and relies on sorting stocks by their prior return (relative strength)[1]. We use U.S. data from Ken French's website[2] to construct the winners portfolio return series from an all-cap U.S. portfolio of the top 30% of relative strength. Similarly, the losers portfolio return is the return of an all-cap U.S. portfolio of the bottom 30% of relative strength stocks. WML is the strategy that buys this winners portfolio and shorts this losers portfolio. In academic literature, the term 'momentum *crash'* is synonymous with the WML strategy experiencing a period of significant losses. For the WML strategy to experience a drawdown either the winners underperform, the losers outperform, or both simultaneously occur. In our analysis, we find that the losers outperforming is what causes the momentum factor (WML) *crashes*, while the winners underperforming is far less of a contributor.

Figure 1 displays histograms of monthly returns along with probability density estimates[3], shown as a dashed line, for WML, the winners portfolio excess to the market, and the losers portfolio excess to the market portfolio returns. As can be seen in the figure, the left tail of the distribution extends the farthest for the WML portfolio, indicating its propensity to suffer major declines. On the other hand, the left tail of the winners portfolio is far less dramatic.

Meanwhile, the right tail of the losers portfolio distribution extends dramatically to the right (approaching 50% before going to zero), indicating the non-zero probability of the losers to experience occasional extreme upside performance, contributing to the WML portfolio *crashes*. As a robustness check, we also compute the density estimates for non-U.S. market data in Appendix 1 and find similar results.
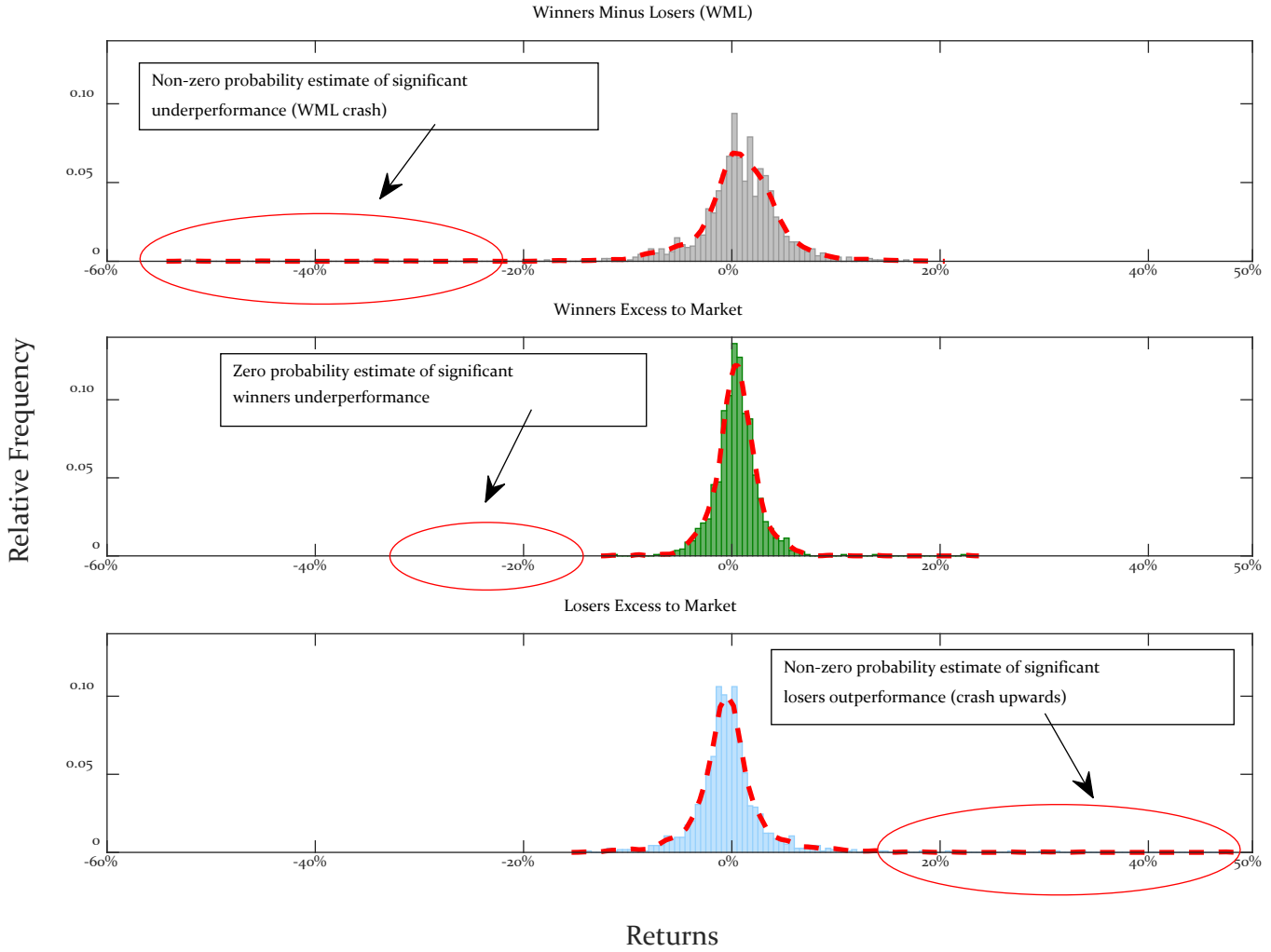
---

[1] The standard momentum sort uses the trailing eleven-month total return lagged by one month.

[2] The period studied is, 1926-2021, and the data may be found at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The winners portfolio return series which is the average return of the top 30% of relative strength intersected with a large cap and a small cap portfolio. Similarly, the losers portfolio return is the average return of the bottom 30% of relative strength stocks intersected with a large and a small cap portfolio.

[3] We plot a nonparametric representation of the probability density function using a smoothing kernel.

Figure 1: Histogram and Probability Density Plots
January 1927 – December 2021

Winners Minus Losers (WML)

Non-zero probability estimate of significant underperformance (WML crash)

Winners Excess to Market

Zero probability estimate of significant winners underperformance

Relative Frequency

Losers Excess to Market

Non-zero probability estimate of significant losers outperformance (crash upwards)

Returns

Identifying the crashes

Figure 2 displays the growth through time of these portfolios (WML, Winners, Losers) along with the market portfolio. The red dots indicate the fifteen worst months for the momentum (WML) strategy. As the dots indicate, the worst months for the WML portfolio tend to cluster[4] and typically occur after a two-year market decline and the subsequent market rebound.

Figure 2: Growth of Winners, Losers, WML, and the Market
January 1927 – December 2021

Growth of $1 Million

---
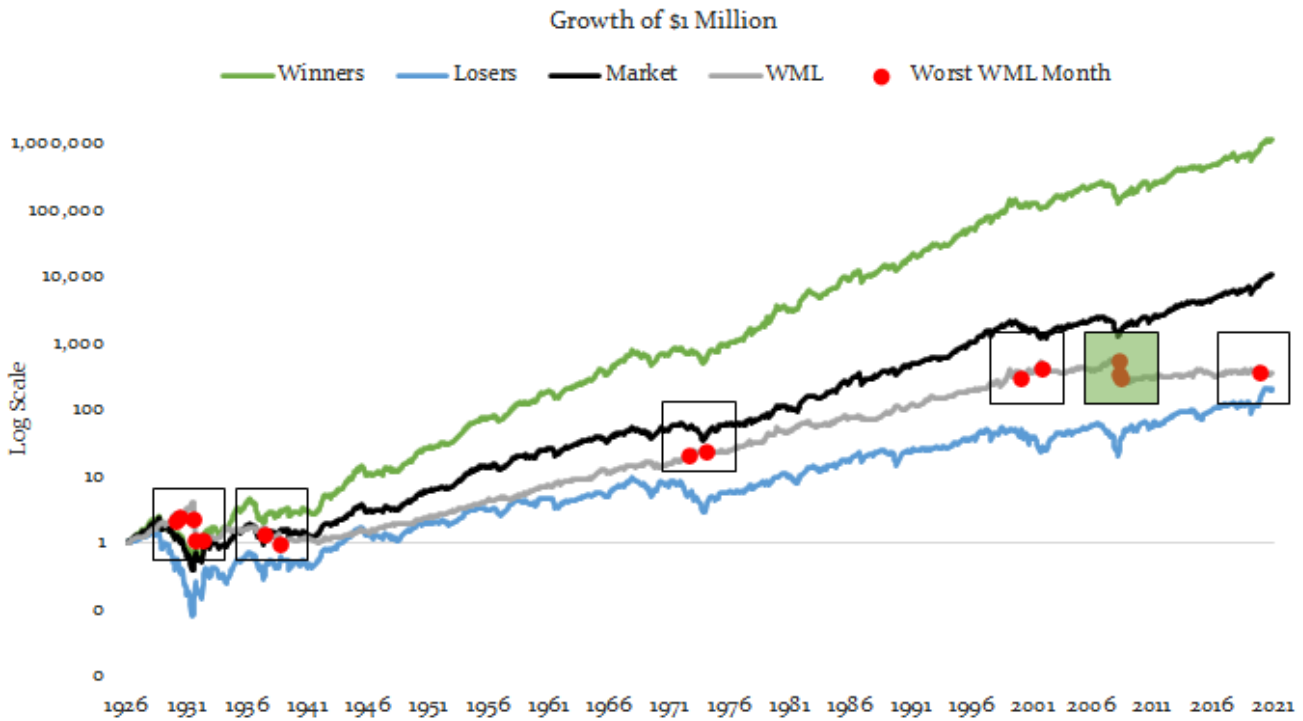
[4] We denote the clusters with rectangles and zoom in on each of these time-periods in Figure 3 and Appendix A2.

Table 1 displays the data of the drawdowns corresponding to these fifteen worst months for the WML portfolio and the other portfolios from Figure 2. As noted in the table, these drawdowns for the WML portfolio can be substantial, ranging from losses of 12% to 52%. In almost every one of the WML's worst months, the market begins the month in market decline (as measured by the highly negative trailing 2-year market return column) and is rebounding in the current month (as measured by the highly positive market return column). During these momentum *crash* months, it is the losers portfolio that does extremely well, driving the losses in the WML portfolio.

Notably, the winners portfolio is positive for the most part and experiences far less of a drawdown relative to the market. Still, the winners can't keep up with the losers portfolio in these market rebounds. However, in the 15 worst months for momentum *crashes* (WML), the combination of a winners long-only portfolio and a value portfolio does not suffer a decline relative to the market in 73% of the observations (winners + value excess to market column). Furthermore, in those months where it does suffer a decline, its excess losses are quite mild.

Table 1: The Fifteen Worst Months for WML

Year-Month	WML	Winners	Losers	Market	Winners Excess to Market	Losers Excess to Market	Winners + Value Excess to Market	Preceeding 2-Year Market Return
1932-08	-52%	32%	84%	37%	-5%	47%	16%	-68%
1932-07	-45%	23%	68%	34%	-11%	34%	10%	-75%
2009-04	-34%	6%	40%	10%	-4%	30%	1%	-41%
1939-09	-31%	17%	48%	17%	0%	31%	16%	-22%
2001-01	-25%	-1%	25%	4%	-4%	21%	-3%	11%
1938-06	-25%	17%	42%	24%	-6%	18%	-1%	-28%
1931-06	-18%	10%	28%	14%	-4%	14%	2%	-48%
1933-04	-17%	39%	56%	39%	0%	17%	9%	-59%
2002-11	-16%	1%	17%	6%	-5%	11%	-2%	-36%
1931-02	-14%	9%	24%	11%	-2%	13%	1%	-39%
1975-01	-14%	15%	29%	14%	1%	15%	6%	-42%
2009-05	-12%	2%	15%	5%	-3%	9%	-2%	-37%
2020-11	-12%	14%	27%	12%	2%	14%	4%	27%
2009-03	-12%	7%	19%	9%	-2%	10%	0%	-45%
1973-07	-12%	5%	17%	6%	-1%	11%	0%	3%

Portfolios are calculated using data from Ken French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html The Momentum (or Value) portfolio returns are formed as the average return over the top 30% by prior return (or B/M for value) intersected with a large cap and a small cap portfolio. The Market portfolio return represents the cap-weighted entire universe of stocks return and the winners/value combination is the equally-weighted winners portfolio return with the value portfolio return. Please see Important Disclosures at the end of this document.

Anatomy of a crash

The clustering of the red dots in Figure 2 allows us to drill down on some of the worst momentum crashes. We show in Figure 3, the time-period associated with the green-box of Figure 2, the three-year sub-sample period around the financial crisis (2009-2011)[5]. As can be seen in Figure 3, the losers (blue line) rise sharply during the red-dot months, outperforming both the market and the winners. In Table 2, we show the amount of outperformance by the losers during these three worst months for WML, and the annualized performance (and excess returns) over the entire three-year period for each strategy. Notably, these WML crash months coincide with large losers portfolio gains. Namely, during the Great Financial Crisis worst WML months of March 2009 through May 2009, the winners returned 15% while the losers returned 90%. However, while the winners portfolio can't keep pace with the losers portfolio in these months, its setback relative to the market portfolio is less dramatic. Further, the winners portfolio begins recovering relative to the market after these worst months and trails by only 212 bps. annualized over the entire 3-year period around the Great Financial Crisis.

Figure 3: Growth of Winners, Losers, and the Market During the Great Financial Crisis
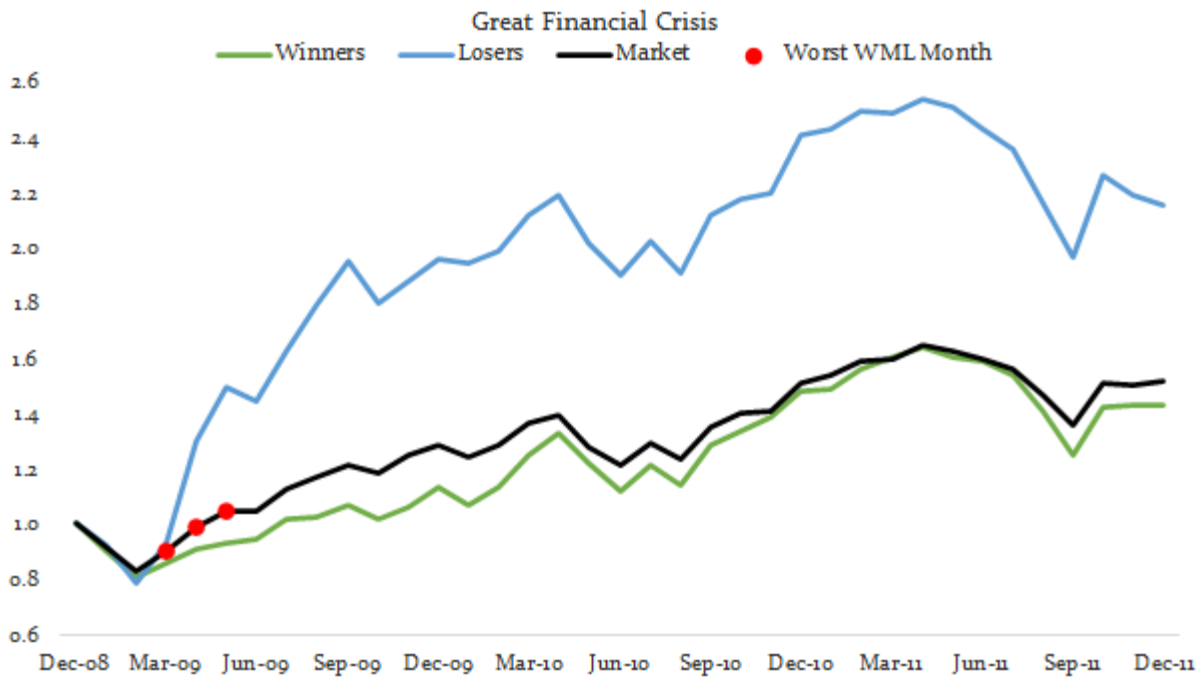January 2009 – December 2011

Table 2: Returns of Winners, Losers, and the Market During the Great Financial Crisis
January 2009 – December 2011

| Great Financial Crisis	Winners	Losers	Market
3-Month Return Over March 2009 - May 2009	15%	90%	26%
Annualized Return Over 2009-2011	13%	29%	15%
Annualized Excess Return Over 2009-2011	-2%	14%	--

[5] We show in Appendix 2, the remaining red dots in Figure 2 in the sub-sample charts and tables containing: the three-year sub-sample periods around the great depression (1931-1933), the dot com bubble (2001-2003), the most recent time-period (2019-2021), the oil crisis (1973-1975), and the recession-new deal (1938-1940). These five charts and tables depict similar results.

The cause of the crashes

We find that momentum (WML) crashes occur following multi-year market drawdowns (accompanied by periods of high market volatility[6]) as the market rebounds. When market drawdowns occur, stocks that do well tend to be low beta stocks and the winners portfolio itself becomes low beta. The WML strategy also underweights high beta stocks (or shorts high beta stocks) during the drawdown. When the market quickly rises after these drawdowns, low beta stocks tend to underperform, while the high beta stocks outperform as market participants seek to benefit from a market resurgence. This dynamic causes momentum strategies to *crash*. To quantify this, we follow Daniel and Moskowitz (2016) and estimate two regression specifications. The first which we detail in Appendix 3, is computing rolling two-year exposures to the market (beta) using daily stock returns[7]. This measure allows us to capture the market exposure over several days and make the comparison shown in Figure 4, between the betas for the winners and the losers portfolios through time.

The market return (in black) is the annualized trailing 2-year return and measures the crash states. In all seven labeled market crash states (where the market return was negative for an extended period), we see that the spread between the beta of the losers portfolio and the beta of the winners portfolio widens. The blue line rises while the green line falls as the losers portfolio beta is much larger than the winners portfolio beta. This dynamic is the cause of the WML crash. When the market rebounds, the losers side of the WML portfolio crashes upwards, and since WML shorts it, it accounts for much of the underperformance of the WML strategy.

Figure 4: Beta Exposures to the Market Portfolio
January 1927 – December 2021

Rolling 2-Year Market Exposures and Rolling 2-Year Annualized Market Return

---
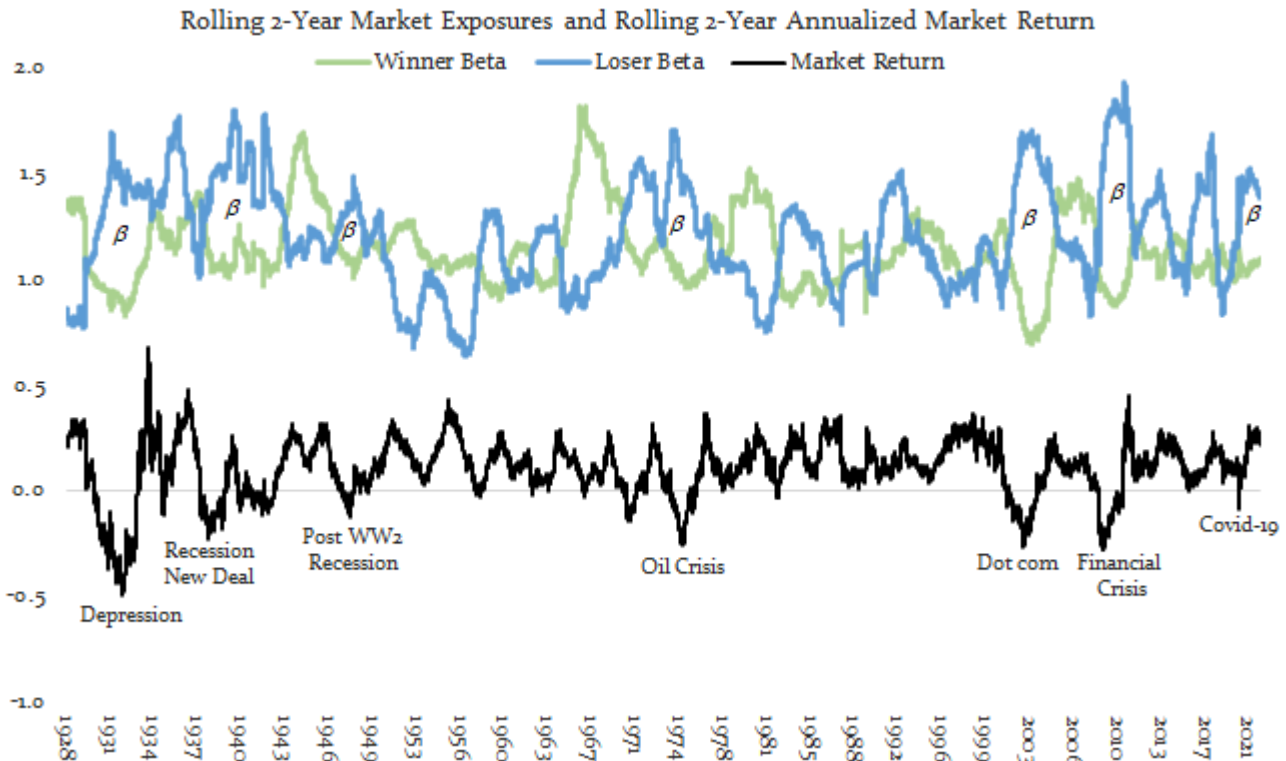
[6] See Asness et al. (2014), Momentum myth number eight.
[7] The regression specification uses the current market return and ten daily lags to estimate eleven exposures. We then sum over the eleven betas to obtain the full market exposure by allowing for information being incorporated during multiple days.

Appendix 3 also discusses a second regression specification which provides further evidence of the beta rising on the short side during periods of market drawdowns. It also shows that combining the winners side with value allows for the combination portfolio to increase its beta in panic states and capture more of the market rebound performance than that of the winners side alone.

Conclusions and Implementation

Over long periods of time, momentum (WML) is a successful strategy. However, following multi-year market drawdowns usually coinciding with periods of high volatility, the short side (losers) of the portfolio increases its beta to the market. Thus, when the market sharply rebounds, the short side crashes upwards causing WML momentum crashes. This dynamic looks to be the origin of the negative connotations relating to momentum-based strategies. However, we find that the worst effects of a momentum crash can be mitigated by avoiding the shorting of the losers side of the strategy and focusing instead on the winners portfolio (long only momentum), which is far less impacted during these manic market rebounds. Further, by combining the winners portfolio with a long-only value portfolio, the risk of a momentum crash is nearly fully mitigated as the value portfolio helps hedge the short-beta risk of the winners portfolio in market rebounds.

Appendix 1: Histograms and Probability Density Plots

Figure A1.1 and A1.2 show the histograms and density plots for WML, the winners portfolio excess to the market return, and the losers portfolio excess to the market returns across the country groupings associated with the developed markets (23 countries), the developed markets ex U.S., North America, Europe, Japan, and Asia Pacific ex Japan. The data is from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and covers November 1990 – December 2021. The dashed line represents a nonparametric representation of the probability density function using a smoothing kernel. In all plots the following hold:

a. The WML distribution is more spread out than the winner's or loser's excess return distribution.
b. WML's distribution exhibits heavier tails and has a higher probability of exhibiting crash type events (rectangles on the top row).
c. The winner's distribution is centered further to the right than the loser's distribution.
d. The loser's density function estimates have positive probability estimates extending to the far right (positive chance of crashing upwards; rectangles on the bottom row) while the winners do not have positive probability estimates extending to the far left (not a positive probability estimate of as extreme crashes downward; rectangles on the middle row).

Figure A1.1: Histogram and Probability Density Plots: Global Developed Markets
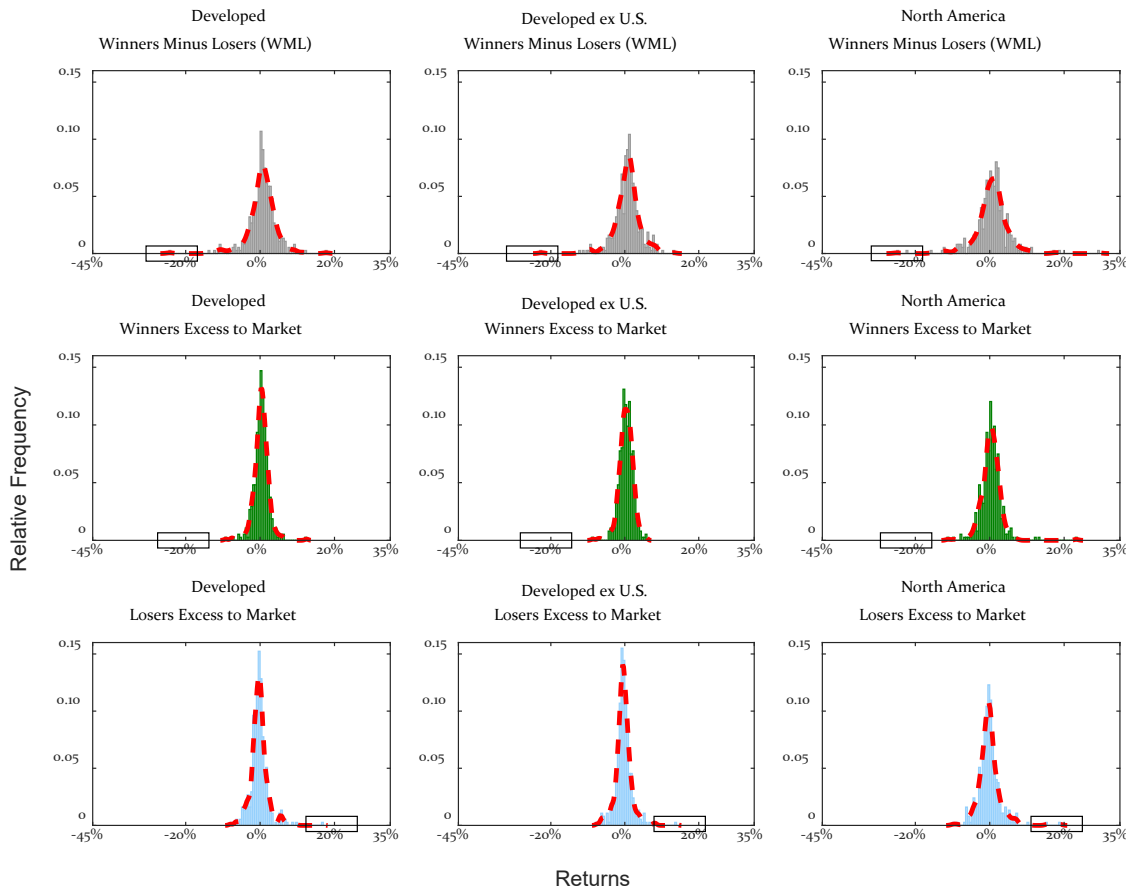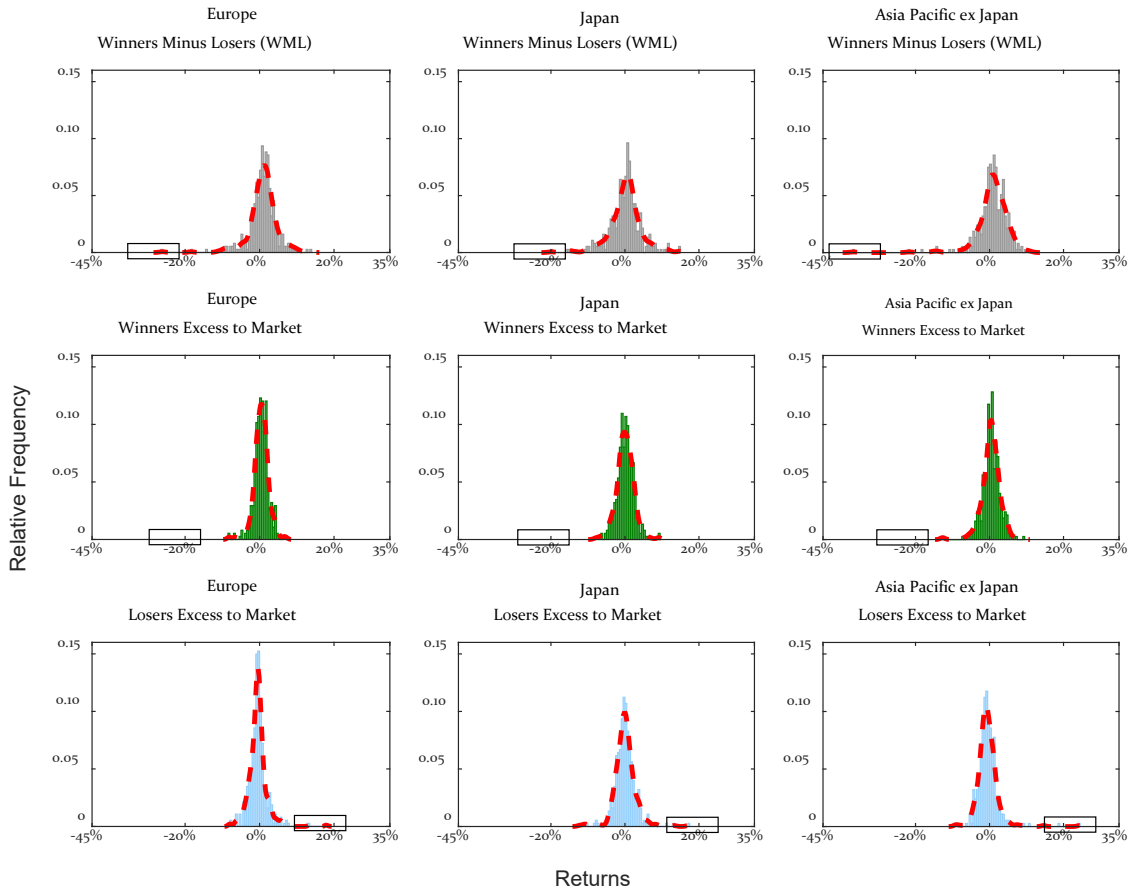November 1990 – December 2021

Figure A1.2: Histogram and Probability Density Plots: International
November 1990 – December 2021

Appendix 2: Anatomy of a Crash

The red dots represent the remaining worst WML months from Table 1. The sub-sample charts and tables contain the great depression (1931-1933), the dot com bubble (2001-2003), the most recent time-period (2019-2021), the oil crisis (1973-1975), and the recession-new deal (1938-1940). The results are very similar to those found earlier in the paper during the great financial crisis.

During the Dot Com Bubble period of the two months Jan 2001 and November 2002, the winners portfolio return was flat while the losers portfolio return was 46%. For the three-year period however, the winners outperformed the market by an annualized 13%.

Figure A2.1: Growth of Winners, Losers, and the Market During the Dot Com Bubble
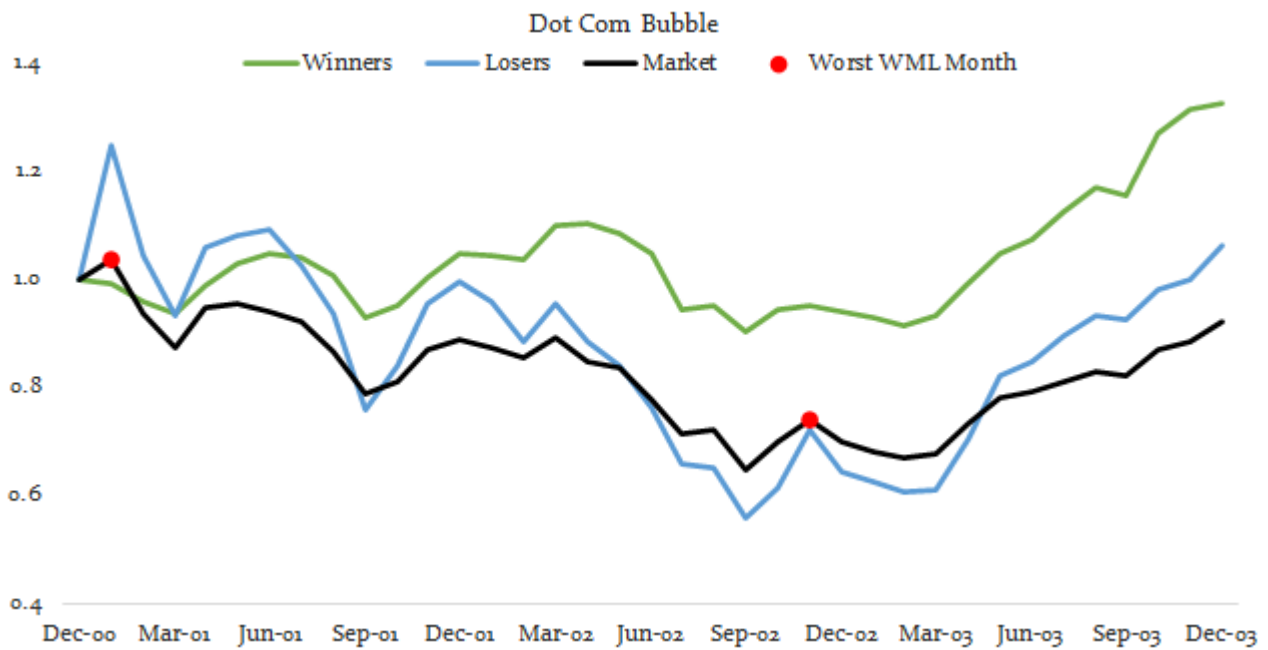January 2001 – December 2003

Table A2.1: Returns of Winners, Losers, and the Market During the Dot Com Bubble
January 2001 – December 2003

Dot Com Bubble	Winners	Losers	Market
Return During Jan. 2001 and Nov. 2002 (2 mon.)	0%	46%	10%
Annualized Return Over 2001-2003	10%	2%	-3%
Annualized Excess Return Over 2001-2003	13%	5%	--

The Great Depression posed great difficulty to the winners. This three-year period contained five of the fifteen worst WML crash months. During Feb. 1931, June 1931, July 1932 - August 1932, and April 1933 (5 mon.) the winners returned 170% and the losers returned 659%. True to form, the winners portfolio excess return for the three-year period recovered nicely and outperformed the market by an annualized 11%.

Figure A2.2: Growth of Winners, Losers, and the Market During the Great Depression
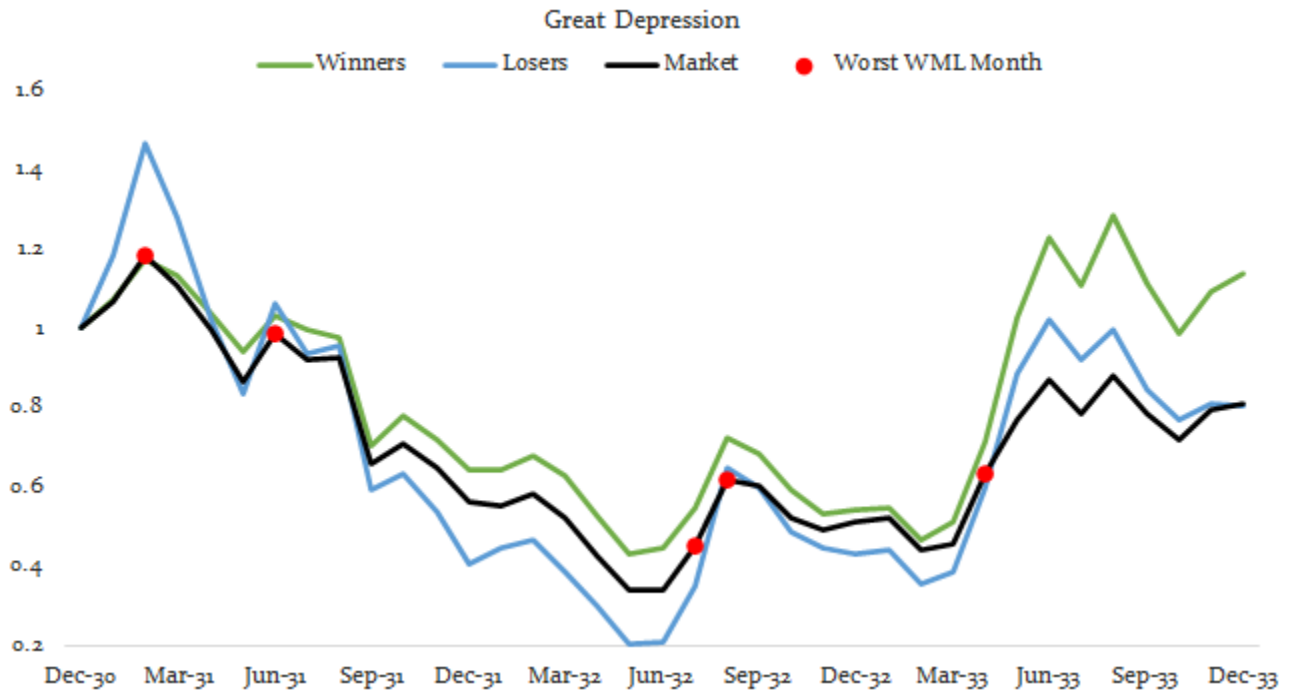
January 1931 – December 1933

Table A2.2: Returns of Winners, Losers, and the Market During the Great Depression

January 1931 – December 1933

Great Depression	Winners	Losers	Market
Return During Feb. 1931, Jun. 1931, and Jul. 1932 - Aug. 1932, and Apr. 1933 (5 mon.)	170%	659%	222%
Annualized Return Over 1931-1933	4%	-7%	-7%
Annualized Excess Return Over 1931-1933	11%	0%	--

Figure A2.3: Growth During the Most Recent Period
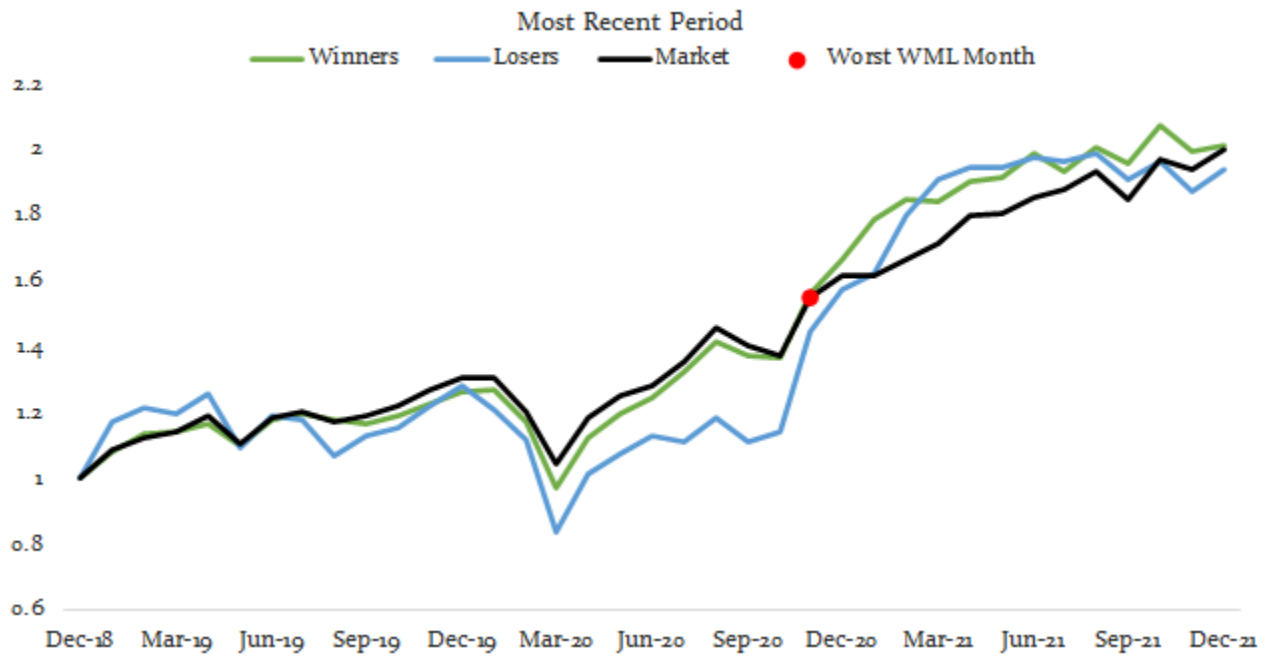### January 2019 – December 2021

Table A2.3: Returns of Winners, Losers, and the Market During the Most Recent Period
January 2019– December 2021

Most Recent Period	Winners	Losers	Market
Return Over Nov. 2020 (1 mon.)	14%	27%	12%
Annualized Return Over 2019-2021	26%	25%	26%
Annualized Excess Return Over 2019-2021	0%	-1%	--

Figure A2.4: Growth During the Oil Crisis
January 1973 – December 1975

Oil Crisis
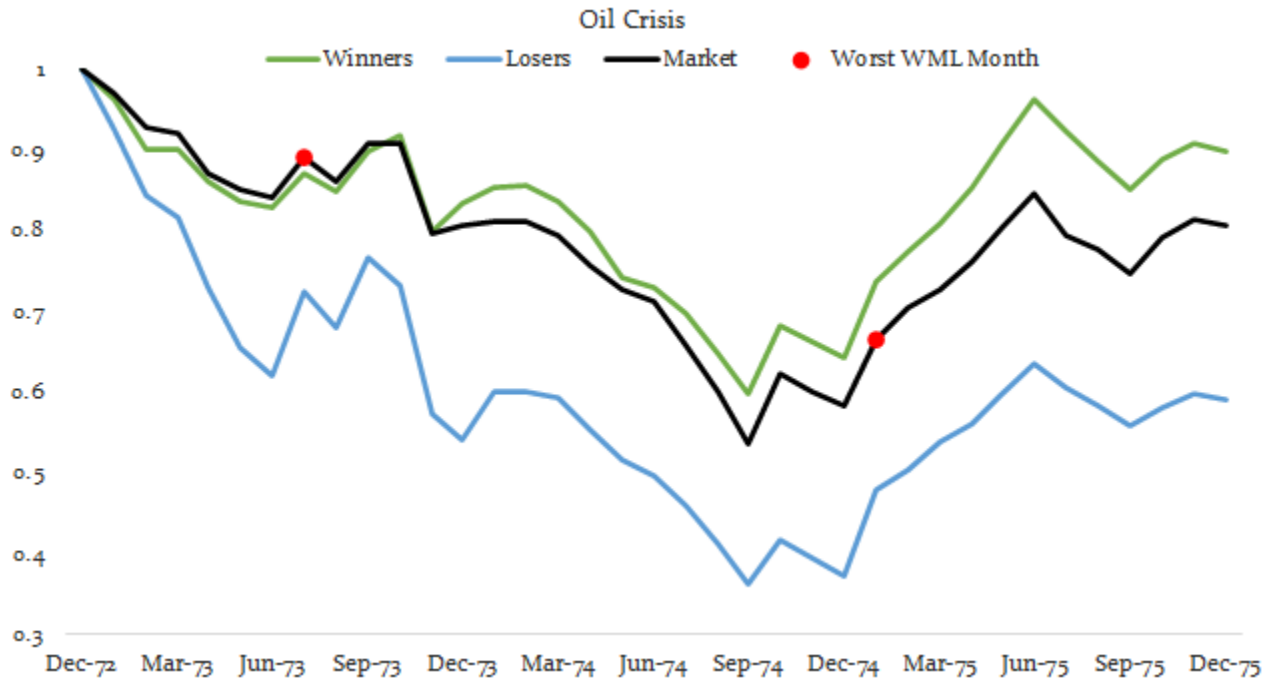
—Winners —Losers —Market ● Worst WML Month

Table A2.4: Returns of Winners, Losers, and the Market During the Oil Crisis
January 1973 – December 1975

Oil Crisis	Winners	Losers	Market
Return Over July 1973 and Jan 1975 (2 mon.)	21%	50%	21%
Annualized Return Over 1973-1975	-3%	-16%	-7%
Annualized Excess Return Over 1973-1975	3%	-9%	--

Figure A2.5: Growth During the Recession – New Deal Period
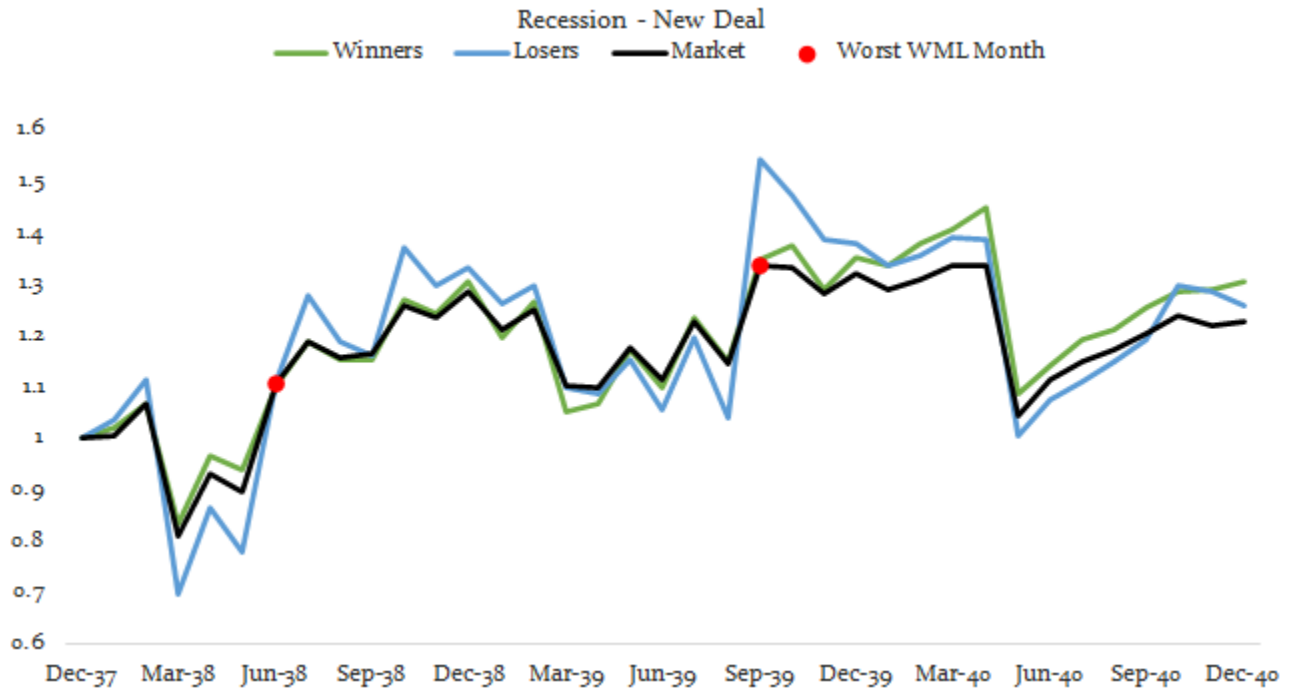
January 1938 – December 1940

Table A2.5: Returns of Winners, Losers, and the Market During the Recession – New Deal Period

January 1938 – December 1940

Recession - New Deal	Winners	Losers	Market
Return Over June 1938 and Sept. 1939 (2 mon.)	38%	111%	45%
Annualized Return Over 1938-1940	9%	8%	7%
Annualized Excess Return Over 1938-1940	2%	1%	--

Appendix 3: Rolling Two-Year Beta and Market Crash Indicator Regressions

We compute rolling two-year market exposures (beta) using daily data. The 504-day time series regression uses the contemporaneous market return as well as ten daily market return lags. Due to information being incorporated during multiple days we use the following specification and report the beta exposure as the sum over the eleven indexed betas:

$$R_t^e = \beta_0 M_t^e + \beta_1 M_{t-1}^e + \ldots + \beta_{10} M_{t-10}^e + \eta_t;$$
$$\beta = (\beta_0 + \beta_1 + \ldots + \beta_{10}).$$

(1)

This specification is also used in Daniel and Moskowitz (2016). The superscript, e, denotes returns in excess of the risk-free rate, the dependent variable is either the winners or losers returns, and the right-hand side M variable represents the market return.

CAPM and CAPM-Conditional on market crash regression specifications:

$$R_t^e = \alpha + \beta_{CAPM} \cdot M_t^e + \varepsilon_t;$$
$$R_t^e = \left(\alpha_0 + \alpha_C \cdot 1_{[C_{t-1}<0]}\right) + \left(\beta_0 + \beta_C \cdot 1_{[C_{t-1}<0]}\right) M_t^e + \gamma_t.$$

(2)

This decomposition is also found in Daniel and Moskowitz (2016). The dependent variables and the market return are all in excess of the risk-free rate, with the exception of WML. The coefficients are estimated using OLS and both equations in (2) are estimated separately using monthly time-series regressions. The time-period covered is 1927-2021. The crash indicator variable, $1_{[C_{t-1}<0]}$, is one if the market return over the trailing two years (t-24, t-1) is negative and zero otherwise. The market return, M, is contemporaneous with that of the left hand-side variable. We report in Table A3.1 the intercepts (as percentages) along with the beta estimates, and below each coefficient we include the associated t-stat.

Table A3.1: CAPM and CAPM Conditional on Market Crashes

Capital Asset Pricing Model		Dependent Variable			
		WML	Winners	Losers	Winners and Value
Intercept	α	0.82	0.41	-0.41	0.30
T-Stat	$t(\alpha)$	6.11	6.28	-3.93	4.56
Market	β_{CAPM}	-0.31	1.08	1.39	1.17
T-Stat	$t(\beta_{CAPM})$	-12.51	89.66	71.24	97.05
Adjusted R-squared	R^2	0.12	0.88	0.82	0.89
Capital Asset Pricing Model - Conditional on Crashes					
Intercept	α_0	0.87	0.35	-0.51	0.27
T-Stat	$t(\alpha_0)$	6.50	5.05	-4.82	3.78
Intercept-Conditional on Crash	α_C	-1.08	0.07	1.16	0.26
T-Stat	$t(\alpha_C)$	-3.32	0.43	4.44	1.48
Market	β_0	0.01	1.17	1.17	1.14
T-Stat	$t(\beta_0)$	0.20	73.05	47.70	69.19
Market-Conditional on Crash	β_C	-0.68	-0.21	0.47	0.08
T-Stat	$t(\beta_C)$	-15.13	-8.98	13.04	3.15
Adjusted R-squared	R^2	0.28	0.88	0.85	0.90

In column 3 the WML regressions show, in the CAPM context, that WML generates a large significant premium and displays a negative beta to the market. In the CAPM-conditional on the market crashing regression we see that the crash state reduces the WML premium by 108 basis points (α_C) and is statistically significant. We also find that the market beta is reduced by a significant 0.68 (β_C) during the crash states.

We also consider (in columns 4, 5, and 6) three long-only portfolios: Winners, Losers, and the average of Winners and Value. In all three CAPM regressions we show a significant positive intercept (negative for the losers) and betas to the market above one (the largest beta for the losers). Interestingly during the crash states, the three CAPM conditional regressions show that only the loser's portfolio has a significant change in premium by gaining 116 basis points (α_C). This makes clear that in these crash states the loser side is crashing upwards and causing WML to crash. Fortunately, the winners (α_C) and the winners and value (α_C) does not suffer in this way. The interaction terms from these decompositions show that that the loser's beta significantly increases by 0.47 (β_C) during the crash states leading to trouble for WML during market rebounds. Another source of trouble for WML during market rebounds, although with not as large of magnitude as the losers portfolio, the winners portfolio beta decreases by 0.21 (β_C) during crashes. Pairing the winners with value we see that the crash-state change in beta of 0.08 has ameliorated these issues and is a beneficial way to hedge beta exposure during market rebounds.

About EAM

EAM Investors is solely focused on delivering alpha for clients in global equity markets. Our Informed Momentum approach to investing combines stock selection, tailored risk management, and efficient implementation to effectively deliver the momentum premium. This investment process is the foundation of our firm and is applied consistently across all our strategies. For our clients, we deliver persistent risk exposures, resulting in more consistent and predictable alpha.

About the Authors

Travis Prentice

Travis is CEO and Chief Investment Officer of EAM Investors, a firm he co-founded in 2007. In addition, he is Portfolio Manager for EAM's US and Global strategies, as well as an analyst across all EAM's strategies. Prior to founding EAM, Travis was a Partner, Managing Director and Portfolio Manager with Nicholas-Applegate Capital Management where he had lead portfolio management responsibilities for their Micro and Ultra Micro Cap investment strategies and a senior role in the firm's US Micro/Emerging Growth team. He has 24 years of institutional investment experience specializing in small and micro cap equities. He holds an MBA from San Diego State University and a BA in Economics and a BA in Psychology from the University of Arizona.

David Wroblewski, PhD

David is a Director of Applied Research at EAM Investors. Prior to joining EAM in 2021, David was Director of Research at Denali Advisors, an institutional equity manager with US and Non-US strategies. He has additional experience in research and risk management from Nicholas-Applegate Capital Management. David also serves as an Adjunct Instructor in the Department of Mathematics at San Diego City College. He has over thirteen years of investment experience. David received a Ph.D. in Mathematics at the University of California, San Diego, a Master of Science in Applied Mathematics and a Bachelor of Science in Applied Mathematics from California State University, San Diego. David has published papers in the Journal of Investment Management, Financial Analyst Journal, and Applied Economics, among other financial publications. He has been awarded the "Harry M. Markowitz, Special Distinction Award" from The Journal of Investment Management.

Important Disclosures

The information provided here is for general informational purposes only and should not be considered an individualized recommendation or personalized investment advice. The investment strategies mentioned here may not be suitable for everyone. Each investor needs to review an investment strategy for his or her own particular situation before making any investment decision. All expressions of opinion are subject to change without notice in reaction to shifting market conditions. Data contained herein from third-party providers is obtained from what are considered reliable sources. However, its accuracy, completeness or reliability cannot be guaranteed. Supporting documentation for any claims or statistical information is available upon request. Investing involves risk including loss of principal. Past performance is no guarantee of future results and the opinions presented cannot be viewed as an indicator of future performance.

Fama-French returns referenced in this document are calculated using monthly and daily data from Ken French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The U.S. Market portfolio return represents the return of the U.S. universe of stocks. The Winners portfolio return is the average return over the top 30% prior return intersected with a large and a small cap portfolio. The Losers portfolio return is the average return over the bottom 30% prior return intersected with a large and a small cap portfolio. The Momentum portfolio return is the winners return minus the losers return. The Value portfolio return is the average return over the top 30% Book/Market intersected with a large and a small cap portfolio. The Momentum and Value combination portfolio is equally weighted between momentum and value. The international data is comprised of developed markets and consists of stocks in 23 developed countries. The U.S. Dollar is the currency used to express performance.

References:

Asness, C., Frazzini, A., Israel, R. and Moskowitz, T. "The Fact, Fiction, and Momentum Investing." Journal of Portfolio Management, Special 40th Anniversary Issue (2014), 40 (5) 75-92.

Carhart, M. Mark, "On Persistence in Mutual Fund Performance." The Journal of Finance, (1997), 52: 57-82.

Kent Daniel, Tobias J. Moskowitz, "Momentum crashes." Journal of Financial Economics, Volume 122, Issue 2, (2016), Pages 221-247.