What Does Residual Momentum Tell Us About Firm-Specific Momentum?*

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Abstract

Residual momentum strategies earn significant alphas. The common interpretation for this result—that momentum resides in firm-specific returns—is unwarranted: even in the absence of firm-specific momentum, a strategy sorted on residuals is profitable because it is also a bet against betas. A UMD-like factor that removes these bets to capture true firm-specific momentum earns an alpha of 63 basis points per month (t-value = 9.20). Firm-specific momentum strategies, unlike residual momentum strategies, are almost uncorrelated across regions. Our results indicate that there was a strong firm-specific momentum effect in stock returns until 2002, after which it has been almost fully arbitraged away.

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1 Introduction

Past winners continue to outperform past losers (Jegadeesh and Titman 1993). Momentum is found not only in equities but in most other asset classes.[1] The nature of risks and rewards to momentum investing is not clear. Although winners and losers significantly comove—which suggests that they are exposed to same systematic risks (Carhart 1997; Cochrane 2011)—strategies that select stocks based on their estimated residual returns earn higher risk-adjusted returns than those based on stocks' total returns (Grundy and Martin 2001; Blitz, Huij, and Martens 2011). This finding has been interpreted as suggesting that momentum resides, at least in part, in firm-specific returns. In this paper we show that residual momentum strategies confound firm-specific momentum with a betting-against-beta effect and (omitted) factor momentum, and devise a method for measuring true firm-specific momentum.

Because firm-specific returns are unobservable, researchers sort on residuals estimated from factor models such as the CAPM. This approach assumes that (1) a stock's estimated residual is an unbiased measure of the unobserved firm-specific return and (2) the estimation errors do not correlate with future stock returns. We show that this line of reasoning fails if security factor lines are not sufficiently steep. In this case the alpha from a regression of the residual momentum strategy on factors does not reflect the performance of the true firm-specific momentum. We prove that this alpha is always positive if the security factor lines are too flat, even if the true firm-specific returns are IID.

The CAPM residual momentum strategy illustrates the intuition. Consider a single-factor economy wherein the security market line is flat similar to the U.S. market (Frazzini and Pedersen

[1] Jostova, Nikolova, Philipov, and Stahel (2013), Beyhaghi and Ehsani (2017), Asness, Moskowitz, and Pedersen (2013), Menkhoff, Sarno, Schmeling, and Schrimpf (2012), and Lee, Naranjo, and Sirmans (2014), for example, document momentum in corporate loans and bonds, commodity and currency futures, and credit default swaps.

2014). In this economy high beta assets earn negative alphas and low beta assets earn positive alphas. If so, sorting stocks in portfolios by residuals (or alphas) is the same as doing a reverse sort on the assets' betas. If we regress the return on this strategy on the factor, we must recover a positive alpha; but this is nothing more than the betting-against-beta effect (Black 1972). Residual momentum strategies' alphas are therefore not unbiased measures of the amount of momentum in firm-specific returns.

We find strong empirical support for this argument. Residual momentum alphas display two puzzling attributes. First, the more factors we remove to estimate the residuals, the more the resulting residual momentum strategies covary with the factors we just removed. The behavior in the residual momentum strategies' R^2s suggest that there is something more to these strategies. We would expect residual momentum strategies to become increasingly unmoored from the systematic factors as we remove more and more of these factors from the data to closer to firm-specific returns. In the data the pattern is the opposite. The model's explanatory power increases because a residual momentum strategy that "removes" more factors makes *more* bets against those factor betas.

Second, when we remove more factors, residual momentum average returns decrease but the *alphas* increase. This disconnect between average returns and alphas is a telltale sign of something being amiss. If we had a true firm-specific momentum strategy, this strategy's loadings against all factors and the regression's R^2 should be zero. We show analytically, and demonstrate with simulations, that all these patterns emerge in an economy with flat security factor lines: negative factor loadings, large R^2s, small average returns, and large alphas.

In addition to the betting-against-beta effect, the possibility of missing factors impairs the analysis and interpretation of residual momentum strategies. A factor not among the five Fama-

French factors might display momentum. This momentum carries over to the cross-section of stock returns and would remain lodged in there even after removing the Fama-French factors (Ehsani and Linnainmaa 2020). In short, past residual returns represent a combination past firm-specific returns, past returns to any missing factors, and bets against betas. A sort on past residuals is a sort on these three components. The profits to the residual momentum strategy therefore combine firm-specific momentum, omitted factor momentum, and the betting-against-beta (BAB) strategy. How can we separate the true firm-specific component from the other two effects?

We propose a theoretically motivated four-step approach for extracting firm-specific returns. This procedure removes the beta bets from the estimated residuals, pushing the resulting strategy a step closer to true firm-specific momentum. We use an analytical decomposition of residual momentum returns to propose one efficiency test and two covariation tests for the null hypothesis of momentum in (true) firm-specific returns. We show that firm-specific momentum is present if:

1. The beta-neutral residual momentum strategy (iRMOM) dominates the residual momentum strategy (RMOM) in terms of mean-variance efficiency.

2. The beta-neutral residual momentum strategies covary less across regions than the residual momentum strategies.

3. The beta-neutral residual momentum strategy does not covary with factor momentum strategies.

We find each of these patterns in the data:

1. The standard residual momentum with respect to the Fama-French model has a Sharpe ratio of 0.59 in the U.S. market. The corresponding beta-neutreal strategy's Sharpe ratio is 1.23.

This result holds within each geographic region.

2. The average pairwise correlation between the Fama-French residual momentum strategies from different regions is 0.40 while the same average for the beta-neutral versions is 0.24. The beta-neutral versions correlate less than the original strategies for all pairs of regions.

3. The correlation between the Fama-French residual momentum strategy and factor momentum is 0.36 whereas the correlation between the beta-neutral version and factor momentum is 0.19. That is, there is strong momentum both in factors and firm-specific returns, and strategies designed to capture these effects are almost uncorrelated.

The results from the covariation tests support the view that beta-neutral residual momentum strategies are less systematic (and more firm-specific). The finding that the beta-neutral strategies are far more profitable than the standard strategies is strong evidence of momentum in firm-specific returns.

Our results relate to studies that debate the mechanism that could generate momentum in stock returns. The leading rational[2] and behavioral[3] theories explain momentum either through risk exposures or through the firm-specific channel. Rational models relate past returns of a firm to its future riskiness. Behavioral models use either investor biases or gradual diffusion of information to produce serial correlation in firm-specific returns through under- or over-reaction. Our finding that individual stock momentum stems from both factor momentum and momentum in firm-specific returns is important for this debate. Factor momentum, by definition, *is* about systematic risk and

[2]See, for example, Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007).

[3]See, for example, Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999).

these momentum profits do not display any reversals.[4] We show that the firm-specific momentum profits, by contrast, experience sharp reversals. This pattern supports the view that overreaction followed by a correction likely lies at the root of firm-specific momentum.

The rest of the paper is organized as follows. Section 2 shows that residual momentum strategies have statistical properties that should be absent from firm-specific momentum strategies. Section 3 presents a theoretical decomposition for residual momentum returns and the regression statistics. Section 4 introduces a four-step procedure for constructing a residual momentum strategy that targets momentum in the firm-specific component. Section 5 describes tests for the null hypothesis of no momentum in firm-specific returns and uses simulations to demonstrate how these tests would behave under the null and the alternative hypothesis. Section 6 relates the results to theories of momentum. Section 7 concludes.

2 The residual momentum puzzle

Table 1 shows average returns and Fama and French (2015) five-factor model alphas for a total return and three residual momentum strategies. The total return momentum strategy selects stocks based on their total returns from month $t-12$ to $t-2$. The residual momentum strategies select stocks based on the estimated intercepts from the CAPM and the Fama-French three- and five-factor models. We estimate intercepts by regressing daily excess returns of stocks on the factors of each model over the $t-12$ to $t-2$ period. We include a stock in the sample if it has at least 120 days of returns over the $t-12$ to $t-2$ period, and it has month $t+1$ return. Our momentum

[4]The fact that factor momentum is about factors and therefore systematic does not imply that it must be a rational effect. Ehsani and Linnainmaa (2020) show that a model with persistent investor sentiment and limits to arbitrage, such as Kozak, Nagel, and Santosh (2018), generates an economy with factor momentum.

Table 1: Momentum and Residual Momentum Strategies

This table reports monthly average returns and Fama-French five-factor model alphas for a total return momentum strategy and three residual momentum strategies. The total return momentum strategy selects stocks based on their total returns from month $t-12$ to $t-2$. The residual momentum strategies select stocks based on estimated intercepts from the CAPM and the Fama-French three- and five-factor models over the same time period. We sort stocks into 3×2 value-weighted portfolios based on size (small and big) and the return variable. Each strategy is long the two past winner portfolios and short the two loser portfolios. We rebalance all strategies monthly. The return data on the strategies begin in January 1965 and end in December 2020 ($N = 672$).

	Total return momentum	Residual momentum		
		CAPM	FF3	FF5
Average return, $\bar{r}$	0.56	0.61	0.57	0.50
	(3.56)	(4.33)	(4.77)	(4.39)
Fama-French five-factor model				
Alpha, $\hat{\alpha}_{\text{ff5}}$	0.63	0.74	0.73	0.69
	(4.02)	(5.29)	(6.41)	(6.54)
Factor loadings				
MKTRF	−0.09	−0.10	−0.09	−0.06
	(−2.48)	(−2.99)	(−3.12)	(−2.36)
SMB	0.08	0.05	0.02	0.01
	(1.52)	(1.13)	(0.56)	(0.23)
HML	−0.51	−0.44	−0.44	−0.44
	(−7.13)	(−6.91)	(−8.35)	(−9.16)
RMW	0.09	0.00	0.00	−0.14
	(1.17)	(−0.04)	(0.02)	(−2.72)
CMA	2.14	0.81	−0.63	−0.93
	(0.63)	(0.74)	(0.73)	(0.69)
N	672	672	672	672
Adj. R^2	9.2%	10.4%	17.5%	22.0%

strategies' returns start in January 1965 and end in December 2020.[5]

[5] We construct the momentum strategies using the Carhart (1997) methodology. We sort stocks into 2×3 portfolios based on size and momentum or residual momentum. The size breakpoint is the NYSE median market capitalization and the breakpoints for momentum are the 30th and 70th NYSE percentiles. We compute value-weighted returns for the resulting six portfolios. The residual momentum factor's return is

$$\text{RMOM} = (High_{Small} + High_{Big})/2 - (Low_{Small} + Low_{Big})/2.$$

Table 1 shows that the total return strategy of Carhart (1997) earns a monthly return of 56 basis points (t-value = 3.56). The CAPM residual momentum factor earns a higher average return than UMD, but the average returns then decrease when we move to the three- and five-factor models. The CAPM residual momentum strategy's average return is 61 basis points per month (t-value = 4.33); the average return of the FF5 strategy is 50 basis points per month (t-value = 4.39).

The factor model alphas in Table 1 represent a puzzle. All residual momentum strategies' alphas exceed their average returns. The CAPM residual momentum strategy's alpha is 13 basis points higher than its premium; those of the FF3 and FF5 strategies are 16 and 19 basis points higher. The strategy constructed from the "most" firm-specific returns—the five-factor model alphas—has the highest information ratio (that is, its t-value is the highest) for a five-factor investor. The increasing pattern in these regressions' R^2s constitutes another puzzle: if the residuals net of all factors are orthogonal with respect to the same factors, then a strategy sorted on those residuals should not uncorrelate with the factors. Yet, the strategy constructed from residuals net of all five factors covaries the most with the same factors.

Table 2, which is based on July 1993 through October 2020 sample, shows that these results are specific to neither the early data nor the U.S. market.[6] The left columns show that average momentum profits are statistically significant in Asia Pacific and Europe but not in Japan and North America. The alphas of the total return momentum strategies are close to their average returns. Consistent with the earlier U.S. results, the right columns show that the five-factor model boosts the alphas of the residual momentum strategies based on the same model. In Asia Pacific, for example, the average return on the residual momentum strategy is 84 basis points (t-value =

[6]We use Datastream and Worldscope data for the international markets. We include in our analysis only securities identified as common stocks. We define eligible securities and exchanges and make corrections to the international data using the definitions and rules in Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2019). The international return data for the momentum strategies begin in July 1993 and end in October 2020.

Table 2: Residual Momentum in International Markets

This table reports average monthly returns and Fama-French five-factor model alphas for residual momentum strategies that select stocks based on the estimated alphas from the five-factor models over the $t-12, t-2$ period. We sort stocks into 3×2 value-weighted portfolios based on size and the return variable. Each strategy is long the two past winner portfolios and short the two past loser portfolios. The return data on the strategies begin in July 1993 and end in October 2020 ($N = 328$). The four regions are Asia Pacific (AP), Europe, Japan, and North America (NA).

	Total return momentum					FF5 residual momentum			
	AP	Europe	Japan	NA		AP	Europe	Japan	NA
$\bar{r}$	0.72	0.91	0.21	0.45	$\bar{r}$	0.84	0.70	0.00	0.34
	(2.70)	(4.01)	(0.81)	(1.63)		(4.21)	(4.95)	(0.01)	(1.55)
	Fama-French five-factor model					**Fama-French five-factor model**			
α	0.99	0.76	0.21	0.50	α	1.31	0.89	0.07	0.55
	(3.66)	(3.50)	(0.87)	(1.94)		(6.94)	(6.94)	(0.46)	(3.38)
MKTRF	0.03	−0.13	−0.04	−0.19	MKTRF	0.01	−0.02	0.02	−0.09
	(0.58)	(−2.59)	(−0.87)	(−2.97)		(0.21)	(−0.61)	(0.66)	(−2.19)
SMB	0.32	0.09	−0.07	0.36	SMB	0.23	−0.01	−0.03	0.12
	(3.61)	(0.93)	(−0.79)	(3.66)		(3.75)	(−0.23)	(−0.65)	(2.00)
HML	−0.59	−0.27	−0.32	−0.77	HML	−0.42	−0.43	−0.43	−0.61
	(−5.25)	(−2.16)	(−3.03)	(−6.23)		(−5.30)	(−5.87)	(−6.44)	(−7.91)
RMW	−0.10	0.68	0.44	0.03	RMW	−0.59	−0.19	0.10	−0.35
	(−0.76)	(4.29)	(2.55)	(0.23)		(−6.41)	(−1.98)	(0.88)	(−4.37)
CMA	0.31	0.16	0.01	0.25	CMA	−0.11	−0.32	−0.14	−0.12
	(2.41)	(0.98)	(0.07)	(1.57)		(−1.25)	(−3.41)	(−1.42)	(−1.24)
N	328	328	328	328	N	328	328	328	328
Adj. R^2	13.8%	20.5%	12.9%	21.8%	Adj. R^2	22.7%	30.0%	27.1%	50.8%

4.21), but its alpha 131 basis points (t-value = 6.94). This inflationary effect is the smallest for Japan at 7 basis points. The average difference between alphas and average returns is close to the 20 basis points in Table 1. The other regression statistics in the international data resemble the U.S. results. The factor loadings are more negative and the R^2s higher for the residual momentum strategies than for the total return momentum strategies.

Residual momentum strategies' positive average returns and alphas in Tables 1 and 2 could reflect momentum in missing factors (Ehsani and Linnainmaa 2020). Factors omitted from the five-factor model, for example, will remain embedded in the residuals estimated using this same model. A residual momentum strategy that selects stocks based on these estimated residual will then be an indirect bet on momentum in the missing factors. We test for this hypothesis in Table 3 by controlling for the factor momentum of Ehsani and Linnainmaa (2020). Panel A shows that factor momentum explains all forms of residual momentum in *univariate* regressions. Furthermore, all residual momentum strategies have positive and statistically significant loadings against factor momentum—their t-values range from 10.0 to 16.9—indicating that residual momentum is not really just firm-specific momentum.

Panel B of Table 3 shows that, when we move from the univariate regressions to the five-factor model regressions augmented with factor momentum, the alphas increase substantially. The alpha of the five-factor residual momentum, for example, increases from a statistically insignificant 15 basis points per month to 36 basis points (t-value = 3.48). Ehsani and Linnainmaa (2020, Appendix F) find similar results and conclude that residual momentum strategies are likely "profitable for reasons unrelated to momentum." These other reasons, as we describe below, relate to the flatness of the security factor lines.

3 Analytics of Residual Momentum Strategies

3.1 Residual momentum with no omitted factors

Residual momentum strategies are not pure bets on momentum in *firm-specific* returns. Although residuals are often viewed as being estimates of firm-specific returns, they unavoidably contain bets against the betas of the factor model used to estimate them. As a consequence, when we regress these residual momentum strategies against the first-stage factors, the alpha confounds the true firm-specific momentum strategy with a bet-against-all-factor-betas (BAB) effect. (In this section

Table 3: Explaining Residual Momentum with Factor Momentum

This table reports alphas and factor loadings from time-series regressions of monthly momentum and residual momentum returns. The model is either a univariate model with factor momentum or the Fama-French five-factor model augmented with factor momentum. The data begin in January 1965 and end in Decemeber 2020.

Panel A: Factor momentum (FMOM)

	Total return momentum	Residual momentum CAPM	Residual momentum FF3	Residual momentum FF5
$\hat{\alpha}$	−0.20	−0.05	0.15	0.15
	(−1.43)	(−0.37)	(1.28)	(1.35)
FMOM	3.65	3.16	2.06	1.70
	(17.65)	(16.93)	(11.88)	(9.97)
N	671	671	671	671
Adj. R^2	31.8%	30.0%	17.4%	12.9%

Panel B: Fama and French (2015) model augmented with factor momentum

	Total return momentum	Residual momentum CAPM	Residual momentum FF3	Residual momentum FF5
$\hat{\alpha}$	−0.11	0.09	0.31	0.36
	(−0.83)	(0.75)	(2.90)	(3.48)
FMOM	3.61	3.14	2.05	1.63
	(17.99)	(16.93)	(17.48)	(11.88)
MKTRF	−0.06	−0.07	−0.07	−0.04
	(−1.89)	(−2.50)	(−2.67)	(−1.87)
SMB	0.00	−0.01	−0.02	−0.03
	(0.08)	(−0.35)	(−0.62)	(−0.79)
HML	−0.38	−0.32	−0.36	−0.38
	(−6.35)	(−6.08)	(−7.64)	(−8.48)
RMW	0.16	0.06	0.04	−0.11
	(2.58)	(1.08)	(0.86)	(−2.25)
CMA	0.02	0.00	−0.11	0.00
	(0.22)	(−1.33)	(−2.38)	(−2.40)
N	671	671	671	671
Adj. R^2	38.9%	38.7%	33.9%	33.4%

we assume that the factor model used to estimate the residual is complete; in section 3.2 we assume that the factor model is incomplete.)

To illustrate residual momentum strategy's BAB overlay, assume that a stock's exposure to a single factor f drives the variation of returns in the cross section. Also assume that the factor f betas are not sufficiently priced in the cross section, that is, the price of its beta in the cross section does not equal the factor's time-series premium (Daniel, Mota, Rottke, and Santos 2020). We assume that the trader observes factor f and forms a momentum strategy that selects stocks by their residual returns. We show that the flatness of security factor lines drives a wedge between the residual momentum strategy and the strategy it seeks to approximate, firm-specific momentum.

A stock i's return equals

$$r_i = \eta(\overline{\beta} - \beta_i) + \beta_i f + \epsilon_i, \tag{1}$$

where η determines the flatness of the SML. If $\eta = 0$, intercepts are zero and unconditional returns are fully described by the model. If $\eta > 0$, an asset's alpha declines in its beta, as they do the data both in the U.S. and global markets (Frazzini and Pedersen 2014). The trader estimates the firm-specific return ϵ_i from a time-series regression of asset returns on factor f,

$$\hat{\epsilon}_i = r_i - \hat{\beta}_i f, \tag{2}$$

where $\hat{\beta}_i$ and $\hat{\epsilon}_i$ are the asset's estimated beta and residual. We assume that any estimation errors in the betas are negligible and of second-order importance, $\hat{\beta}_i \approx \beta_i$, to focus cleanly on the betting-against-beta effect. Although this procedure aims to extract the firm-specific return component, the estimated residuals are biased estimates of the firm-specific returns when $\eta \neq 0$:

$$\hat{\epsilon}_i = r_i - \beta_i f = \alpha_i + \epsilon_i = \eta(\overline{\beta} - \beta_i) + \epsilon_i. \tag{3}$$

When the security factor line is too flat ($\eta > 0$), $\hat{\epsilon}_i$ has a positive bias among low-beta assets and negative bias for high-beta assets. This bias works its way into the residual momentum strategy. We first define a betting-against-beta strategy as in Frazzini and Pedersen (2014),[7]

$$\text{Betting-against-beta, BAB}_t \quad = \quad \sum_{i=1}^{N} (\bar{\beta} - \beta_i)(r_{i,t} - \bar{r}_t). \tag{4}$$

This strategy weighs stocks proportional to the estimated betas (which are assumed to have no estimation errors), buying stocks with below-average betas selling those with above-average betas.

The residual momentum strategies buy assets with high $\hat{\epsilon}_i$s and sell assets with low $\hat{\epsilon}_i$s. We assume that the trader employs the Lo and MacKinlay (1990) rule that weighs individual assets in proportion to their past (residual) returns,

$$\text{RMOM}_t \quad = \quad \sum_{i=1}^{N} (\hat{\epsilon}_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t), \tag{5}$$

where $\bar{\epsilon}_{t-1}$ is the cross-sectional average residual. The strategies in equations (4) and (5) are

[7] Because the strategy in (4) is self-financing—by the virtue of subtracting the cross-sectional mean in the weight term—each strategy can also be written without the $\bar{r}_t$ term. For example, $\sum_{i=1}^{N} (\bar{\beta} - \beta_i)(r_{i,t} - \bar{r}_t) \equiv \sum_{i=1}^{N} (\bar{\beta} - \beta_i) r_{i,t}$. We use these definitions interchangeably.

self-financing. The return to the position in stock i is

$$\begin{aligned}
\widehat{\text{RMOM}}_{i,t} &= (\hat{\epsilon}_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t) \\
&= (\alpha_i + \epsilon_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t) \\
&= \eta(\overline{\beta} - \beta_i) \times (r_{i,t} - \bar{r}_t) + (\epsilon_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t). \qquad (6)
\end{aligned}$$

Averaging across the N stocks in the cross section,

$$\underbrace{\sum_{i=1}^{N}(\hat{\epsilon}_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t)}_{\substack{\text{Estimated residual} \\ \text{momentum strategy}}} = \underbrace{\sum_{i=1}^{N}(\epsilon_{i,t-1} - \bar{\epsilon}_{t-1}) \times (r_{i,t} - \bar{r}_t)}_{\substack{\text{True firm-specific} \\ \text{momentum strategy}}} + \underbrace{\eta\sum_{i=1}^{N}(\overline{\beta} - \beta_i) \times (r_{i,t} - \bar{r}_t)}_{\substack{\text{Correction factor} \\ \text{(SFL-flatness} \times \text{BAB)}}}. \qquad (7)$$

The residual momentum strategy therefore equals the infeasible firm-specific momentum strategy *plus* the betting-against-beta factor scaled by the security market line multiplier, η.[8] The second term, which is the "correction factor" of Ehsani and Linnainmaa (2021), drives the negative factor loadings and boosts the alphas in the regressions of the residual momentum strategy against first-stage factors.

Suppose we regress the residual momentum strategy on the same factor f:

$$\widehat{\text{RMOM}}_t = \alpha_{\widehat{\text{RMOM}}} + \beta_{\widehat{\text{RMOM}}} f_t + \epsilon_t. \qquad (8)$$

The theoretical slope coefficient is

$$\beta_{\widehat{\text{RMOM}}} = -\eta\sigma^2_{\beta}, \qquad (9)$$

[8] Even though a stock's estimated residual is a biased proxy for its firm-specific returns, the cross-sectional average of all estimated residuals, $\bar{\epsilon}_{t-1}$, is an unbiased measure for the average firm-specific returns because $\sum_{i=1}^{N}(\overline{\beta} - \beta_i) = 0$.

where σ_β^2 is the cross-sectional variance of factor f betas. If the security factor line is too flat, $\eta > 0$, the residual momentum strategy *has to* load negatively on factor f. This negative slope coefficient in turn increases the alpha,

$$\begin{aligned}
\alpha_{\widehat{\mathrm{RMOM}}} &= \mathrm{E}[\widehat{\mathrm{RMOM}}] - \beta_{\widehat{\mathrm{RMOM}}}\mathrm{E}[f_t] \\
&= \alpha_{\mathrm{RMOM}} + \eta(\mu_{\mathrm{BAB}} + \mu_f \sigma_\beta^2) = \alpha_{\mathrm{RMOM}} + \eta(\eta\sigma_\beta^2 - \mu_f\sigma_\beta^2 + \mu_f\sigma_\beta^2) \\
&= \alpha_{\mathrm{RMOM}} + \eta^2\sigma_\beta^2,
\end{aligned} \tag{10}$$

where α_{RMOM} is the alpha of the true firm-specific momentum strategy with respect to factor f. The residual momentum strategy's alpha equals the alpha of the true firm-specific momentum plus another (non-negative) term that is related to the distortion in factor f's security factor line.

This analysis is not specific to a single-factor model. If the investor extracts the residuals from a multifactor model with orthogonal factors, forms the residual momentum strategy, and regresses this strategy against the first-stage factors, the the resulting alpha equals,

$$\alpha_{\widehat{\mathrm{RMOM}}} = \alpha_{\mathrm{RMOM}} + \sum_{f=1}^{F} \eta^2\sigma_\beta^2, \tag{11}$$

where the second term now collects security-factor-line distortions from all factors in the model. Equation (11) explains why the intercept boosts in Table 1 increase from the CAPM residual momentum to the FF5 residual momentum: the alpha increases in the number of factors with security factor lines the investor has in the model.

3.2 Residual momentum with omitted factors

The analysis in the preceding section assumes that the investor knows the true return generating process. In this case only the distortions in the security factor lines add to the residual momentum strategy's alpha. We now assume that, in addition to this feature of asset pricing models, the investor's asset pricing model omits some factors and is therefore incomplete.

We first illustrate the problem by studying the returns to a total momentum strategy and then extend the derivations to the residual momentum strategy. Consider the multi-factor version of the return process in equation (1):

$$r_{i,t} = \sum_{f=1}^{F} \eta_{f,t}(\overline{\beta}_f - \beta_{i,f}) + \sum_{f=1}^{F} \beta_{i,f} f_t + \epsilon_{i,t}, \tag{12}$$

where $\eta_{f,t}$ determines the slope of the SFL.[9] The investor employs the Lo and MacKinlay (1990) trading rule:

$$\mathrm{MOM}_t \quad = \quad \sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{i,t-1})(r_{i,t} - \bar{r}_t). \tag{13}$$

In the absence of factor and residual cross-covariances, using equations (12) in (13) and taking expectation gives

$$\mathrm{E[MOM]} \quad = \quad \underbrace{\sum_{f=1}^{F}\left[\mathrm{cov}(f_{t-1}, f_t)\, \sigma^2_{\beta_f}\right]}_{\text{factor autocovariances}} + \underbrace{\frac{1}{N}\sum_{i=1}^{N}\left[\mathrm{cov}(\varepsilon_{i,-t}, \varepsilon_{i,t})\right]}_{\substack{\text{autocovariances in}\\ \text{firm-specific returns}}} + \underbrace{\sum_{f=1}^{F}(\mu_f - \eta_f)^2 \sigma^2_{\beta_f}}_{\substack{\text{variation in mean returns}\\ \text{due to factor exposures}}}.$$

[9] If the mean flatness of factor f's security factor line, $\eta_{f,t}$, equals the factor's mean return, factor f's security factor line is completely flat and all assets' expected return equal $r_{i,t} = \sum_{f=1}^{F} \overline{\beta}_f \mu_f$. In the CAPM this would mean that every stock's expected return equals that of the market regardless of their betas.

Momentum in individual stock returns therefore represents a combination of factor momentum, firm-specific momentum, and a mean effect related to the flatness of the security factor lines, factor premiums, and the cross-sectional variation in betas. When the security factor lines are completely flat ($\mu = \eta$), all stocks earn the same rate of return and the average return stemming from the last component becomes zero. In this case the last term only injects volatility to the strategy returns.

We next derive the expected returns to a residual momentum strategy. Suppose that the investor knows k out of F factors of the return process, and regresses returns on these known factors estimate residuals,

$$r_{i,t} = \alpha_i + \sum_{f=1}^{k} \beta_{i,f} f_t + \epsilon_{i,t}, \tag{14}$$

and records the residual, $\hat{\alpha}_i + \hat{\epsilon}_{i,t}$, as the sort variable. The estimated residual equals

$$\hat{\alpha}_i + \hat{\epsilon}_{i,t} = \underbrace{\sum_{f=1}^{F} \eta_{f,t}(\overline{\beta}_f - \beta_{i,f})}_{\text{Long-run intercept}} + \underbrace{\sum_{f=k+1}^{F} \beta_{i,f} f_t}_{\text{Missing factors}} + \underbrace{\epsilon_{i,t}}_{\substack{\text{Firm-specific}\\ \text{returns}}}. \tag{15}$$

The investor again weights stocks proportional to their estimated residuals,

$$\widehat{\text{RMOM}}_t = \sum_{i=1}^{N} \big(\hat{\alpha}_i + \hat{\epsilon}_{i,t-1} - \overline{\alpha} + \overline{\epsilon}_{t-1}\big)(r_{i,t} - \bar{r}_t), \tag{16}$$

and earns an expected return of

$$
\begin{aligned}
\mathrm{E}[\widehat{\mathrm{RMOM}}] \;=\; & \underbrace{\sum_{f=k+1}^{F} \left[\operatorname{cov}(f_{t-1}, f_t)\, \sigma^2_{\beta_f}\right]}_{\text{missing factor autocovariances}} + \underbrace{\sum_{f=k+1}^{F} (\mu_f - \eta_f)^2 \sigma^2_{\beta_f}}_{\substack{\text{variation in returns due to} \\ \text{missing factor exposure}}} \\
& + \underbrace{\frac{1}{N} \sum_{i=1}^{N} \left[\operatorname{cov}(\varepsilon_{i,-t}, \varepsilon_{i,t})\right]}_{\substack{\text{autocovariances in} \\ \text{firm-specific returns}}} + \underbrace{\sum_{f=1}^{k} \eta_f (\eta_f - \mu_f) \sigma^2_{\beta_f}}_{\substack{\text{variation in returns due to} \\ \text{known factor SFL slopes}}}.
\end{aligned}
\tag{17}
$$

Equation (17) shows that returns to a residual momentum strategy equals the true firm-specific momentum strategy only when 1) the asset pricing model is complete and 2) the SFLs satisfy the Arbitrage Pricing Theory (that is, $\eta = 0$). Models such as the CAPM and Fama-French three- and five-factor models are likely not complete descriptions of asset returns. In addition, studies such as Daniel, Mota, Rottke, and Santos (2020) show that betas are not sufficiently priced in the cross section. Equation (17) is therefore a reasonable description of the returns to real-life residual momentum strategies.

The key takeaway is that the returns and alphas to residual momentum strategies can combine three components: firm-specific momentum, omitted factor momentum, and the betting-against-beta effects. An analysis of residual momentum strategies' average returns and alphas may therefore not reveal much about the return process.

4 Beta-neutral residual momentum

How can we identify the drivers of the residual momentum strategy without knowing the true factor model? The first step is to construct a residual momentum strategy without the beta bets. The returns to this strategy are either due to firm-specific momentum or omitted factor momentum. We can then design tests that can disentangle these two remaining explanations.

The first step for testing whether firm-specific returns exhibit momentum is to form residuals that do not contain the beta bets. Section 3.1 shows that even if the investor has the complete factor model, residuals embed beta bets if betas are not priced in the cross section according to the Arbitrage Pricing Theory. In the single-factor case, equation (3) shows that the estimated residual equals $\hat{\epsilon}_{i,t} = \alpha_i + \epsilon_{i,t} = \eta(\overline{\beta} - \beta_i) + \epsilon_{i,t}$. We need to remove the beta term from the estimated residuals to get unbiased proxies of firm-specific returns. This beta term is akin to a long-run intercept as it depends only on the stock's beta and not on time t. We remove these beta bets from the estimated residuals using the following procedure:

1. Estimate each stock's residual return ($\hat{\epsilon}_i$) over the $[t-12, t-2]$ period as the intercept from a time-series regression of daily excess returns on factors.

2. Estimate each stock's long-run intercept ($\hat{\alpha_i}$) of each stock at time $t-1$ from a *time-series* regression of daily excess returns on factors using a lookback window over which stock returns are independently distributed.[10]

[10] The idea is to find the window over which stock returns display neither reversals nor momentum. If we regress month t returns on month $t-1$ returns, we typically find reversals (Jegadeesh 1990); if we regress month t returns on returns from month $t-12$ to $t-1$, we typically find momentum (Jegadeesh and Titman 1993); and if we extend the window enough beyond this point, we begin to find reversals (De Bondt and Thaler 1985). We use historical data to find the window at which these patterns cancel out. Starting in 1930, every month t we compute 48 past returns for each stock. Each past return is computed using a different window; the shortest window is $[t-13, t-1]$ and the longest $[t-60, t-1]$. We then form 48 Fama-French type strategies that sort stocks into portfolios using past returns over each of these windows. The IID window in month t is the window at which the cumulative returns to that portfolio since the beginning of the sample (between 1930 and month t) is the closest to zero. The average rolling return to the shortest window (13 months) is always positive because of the momentum effect and average return to the longest window (60 months) is always negative because of long-term reversals. The IID window is the window at which the sign of the average returns turns from positive to negative. For example, on January 1990, the average return to a strategy that sorts on $[t-20, t-1]$ returns between 1930 and December 1989 is slightly positive, and the return to a strategy that sorts on $[t-21, t-1]$ returns over the same time period is slightly negative. The IID window in January 1990 is thus $[t-21, t-1]$. The IID window varies in small range. The average length is 20 months and the minimum and maximum are 17 and 23.

3. Run a *cross-sectional* regression of estimated residuals on estimated IID intercepts (that is, $\hat{\epsilon}_i$ on $\hat{\alpha}_i$) at time $t-1$ and record the residuals of this regression.

4. Construct a beta-neutral momentum strategy by sorting stocks into portfolios at time $t-1$ using the residuals from the regression in step 3 and compute this strategy's month t return.

In Table 4 we report the average returns of strategies constructed from beta-neutral residuals (iRMOM) to those constructed from standard residuals (RMOM). We report the returns to each leg of the strategy as well as the long-minus-short portfolio. Removing the beta bets significantly increases the residual momentum strategies' Sharpe ratios. For example, whereas the standard FF5 residual momentum that trades small stocks earns an average return of 71 basis points per month (t-value = 6.20), the beta-neutral version of this strategy earns an average of 80 basis points (t-value = 10.88). The 75-percentage point increase in the Sharpe ratio stems primarily from the decrease in the strategy's volatility, not from the increase in its mean.[11] This outcome is what we would expect: if the process works in removing the beta bets, its volatility should fall.

The improvements in Sharpe ratios are greater in the cross-section of large stocks. The FF5 iRMOM strategy that trades large stocks earns 149% (= 5.22/2.10) higher Sharpe ratio than the standard RMOM. The overall FF5 iRMOM, which is the average of its small and large versions, earns a t-value of 9.20, equivalent to a Sharpe ratio of 1.23 and 110% higher than that of the standard RMOM. It is important to emphasize that this portfolio is as tradable as the standard residual or total return momentum because the construction method for iRMOM and RMOM (NYSE breakpoints, size breakpoints, value-weighting, etc.) are exactly the same as the UMD factor of Fama and French. The only difference, which is also the driver of the massive increase in

[11] The t-values can be translated into annual Sharpe ratios by dividing by $\sqrt{672/12} = 7.48$, where 672 is the sample length in months.

Table 4: Residual Momentum Strategies With and Without Beta Bets

This table reports average average returns of strategies constructed from beta-neutral residuals (iRMOM) to those constructed from standard residuals (RMOM). Panels A and B are for small and large stocks, defined using the NYSE median as the breakpoint; Panel C is the average of the small and large portfolios.

	Panel A: Small stocks					
	iRMOM			RMOM		
Portfolio	CAPM	FF3	FF5	CAPM	FF3	FF5
Losers	0.32	0.34	0.37	0.35	0.36	0.41
	(1.26)	(1.32)	(1.46)	(1.30)	(1.34)	(1.56)
2	0.85	0.87	0.87	0.75	0.80	0.79
	(4.03)	(4.17)	(4.15)	(3.66)	(3.86)	(3.77)
Winners	1.24	1.21	1.18	1.19	1.14	1.13
	(4.86)	(4.80)	(4.67)	(4.77)	(4.56)	(4.48)
WML_s	0.91	0.88	0.80	0.84	0.78	0.71
	(9.58)	(11.28)	(10.88)	(6.12)	(6.44)	(6.20)
	Panel B: Large stocks					
	iRMOM			RMOM		
	CAPM	FF3	FF5	CAPM	FF3	FF5
Losers	0.40	0.38	0.38	0.41	0.42	0.44
	(2.05)	(1.99)	(2.02)	(1.88)	(2.08)	(2.27)
2	0.50	0.50	0.50	0.51	0.48	0.49
	(3.10)	(3.07)	(3.06)	(3.08)	(2.99)	(3.09)
Winners	0.84	0.82	0.85	0.78	0.78	0.73
	(4.52)	(4.42)	(4.60)	(3.98)	(3.94)	(3.66)
WML_b	0.45	0.44	0.46	0.38	0.36	0.29
	(4.15)	(4.61)	(5.22)	(2.29)	(2.48)	(2.10)
	Panel C: Average of small and large					
WML	0.68	0.66	0.63	0.61	0.57	0.50
	(7.62)	(9.15)	(9.20)	(4.33)	(4.77)	(4.39)

Sharpe ratio, is the absence of beta bets (or long-run intercept bets) in iRMOM.[12]

We next test whether factor momentum explains the premium to the iRMOM strategy. If the alphas in Panel B of Table 3 fully stem from residual momentum's negative factor loadings,

[12] We construct 208 anomalies based on the signals from Open Source Asset Pricing (Chen and Zimmermann 2020) using the Fama and French (2015) 3×2 methodology. We find three anomalies that earn a Sharpe ratio of 1.20 or more: industry information diffusion (Hou 2007), earnings announcement return (Chan, Jegadeesh, and Lakonishok 1996), and earnings forecast disparity (Da and Warachka 2011).

Table 5: Explaining Beta-Neutral Residual Momentum with Factor Momentum

This table reports the estimates from time-series regressions of three beta-neutral residual momentum strategies (iRMOM) on factor momentum (FMOM). The residual momentum strategies sort stocks into portfolios by residuals computed from the CAPM or the Fama-French three- or five-factor models. Section 4 details the method used to remove beta bets from the residual return.

	iRMOM			iRMOM		
	CAPM	FF3	FF5	CAPM	FF3	FF5
$\hat{\alpha}$	0.38	0.53	0.52	0.33	0.51	0.51
	(4.41)	(7.18)	(7.32)	(3.76)	(6.63)	(6.99)
FMOM	1.43	0.60	0.54	1.43	0.58	0.48
	(10.97)	(5.38)	(5.04)	(10.82)	(5.06)	(4.44)
FF5	N	N	N	Y	Y	Y
Adj. R^2	15.2%	4.2%	3.7%	18.5%	6.5%	6.2%

then factor momentum should explain the premium to iRMOM. Table 5 shows the results from the regressions of iRMOM on factor momentum. iRMOM continues to load on factor momentum. For example, the coefficient from a regression of FF5 iRMOM on factor momentum is 0.54 (with a t-value of 5.04). Nevertheless, this coefficient is a third of the coefficient from the regression of standard FF5 RMOM on factor momentum (the coefficient is 1.70 with a t-value of 9.97 in Table 3). The smaller loadings of iRMOM on factor momentum together with its higher intercepts indicate that factor momentum does not explain iRMOM.

The columns on the right show that controlling for factors does not change the regression statistics. We do not report the factor loadings because they are generally small and insignificant. As a result, intercepts from univariate or multivariate regressions of iRMOM on factor momentum are indistinguishable, suggesting that our approach has purged the beta bets of the residual momentum strategy effectively. iRMOM is indeed one step closer to the (true) firm-specific momentum.

To summarize the results in Tables 4 and 5, we find that removing the intercepts of residual momentum isolates its beta bets, increases its Sharpe ratio, and reduces its covariation with factor momentum. These results seem to support of the presence of firm-specific momentum. However, there is a possibility that the factor momentum in Ehsani and Linnainmaa (2020) that trades momentum using the main principal components of the 50 anomaly portfolios of Kozak, Nagel, and Santosh (2020) is not ideal. Suppose there are important factors in addition to those of Fama and French (2015) and Kozak, Nagel, and Santosh (2020). The returns to the FF5 iRMOM strategy will be a reflection of autocorrelation in those undiscovered factors. Since these factors are missing from Kozak, Nagel, and Santosh (2020), the factor momentum constructed from the portfolios in Kozak, Nagel, and Santosh (2020) will fail to fully capture the returns to FF5 iRMOM. Although the probability of this scenario—that there are several important undiscovered factors beyond Fama and French (2015) and Kozak, Nagel, and Santosh (2020)—seems low, the next section designs simulations to investigate this possibility: how does an iRMOM that owes its return to omitted factors differ from an alternative iRMOM that originates from firm-specific momentum?

5 Does the return to iRMOM reflect firm-specific momentum or momentum in missing factors?

5.1 Economies with factor momentum, flat-SFLs, and firm-specific momentum

We consider four economies to study the behavior of residual momentums. All the four economies exhibit factor momentum ($\text{cov}(f_{t-1}, f_t) > 0$) but are different in whether they exhibit firm-specific momentum, have flat SFLs, or both. The process for each economy is as follows:

$$
\begin{aligned}
\text{FMOM}: r_{i,t} &= \sum_{f=1}^{F} \beta_{i,f} f_t + \epsilon_{i,t}, \quad \rho_{\epsilon_{i,t-1},\epsilon_{i,t}} = 0 && (18)\\
\text{FMOM+RMOM}: r_{i,t} &= \sum_{f=1}^{F} \beta_{i,f} f_t + \epsilon_{i,t}, \quad \rho_{\epsilon_{i,t-1},\epsilon_{i,t}} > 0 && (19)\\
\text{FMOM+BAB}: r_{i,t} &= \sum_{f=1}^{F} \eta_{f,t}(\overline{\beta}_f - \beta_{i,f}) + \sum_{f=1}^{F} \beta_{i,f} f_t + \epsilon_{i,t}, \quad \rho_{\epsilon_{i,t-1},\epsilon_{i,t}} = 0 && (20)\\
\text{FMOM+RMOM+BAB}: r_{i,t} &= \sum_{f=1}^{F} \eta_{f,t}(\overline{\beta}_f - \beta_{i,f}) + \sum_{f=1}^{F} \beta_{i,f} f_t + \epsilon_{i,t}, \quad \rho_{\epsilon_{i,t-1},\epsilon_{i,t}} > 0 && (21)
\end{aligned}
$$

Equations (18), (19), and (20) are special cases of the last equation. The economies share the same factors. In each iteration we draw five factor returns spanning 660 months of data that have similar distribution properties to the Fama-French factors. The simulated factors earn average monthly returns of 0.2% a month at a standard deviation of 2%, and have a first-order serial correlation coefficient of 0.10. We use the five factors to create the systematic component cross-section of returns. The cross-section has 100 stocks. Each stock has exposure to the five factors through its betas that are drawn from a normal distribution $\beta_f \sim N(1, 2)$. The systematic component of return at time t is the factor f beta of each asset times the return of the associated factor summed across five factors. All economies share these traits which means that the systematic returns of all four economies ($\sum_{f=1}^{F} \beta_{i,f} f_t$) are the same.

The **FMOM** economy adds IID firm-specific return to the systematic return. We draw the IID returns from a normal distribution, $\epsilon_i \sim N(0, U(5, 10))$, in which $U(5, 10)$ denotes the continuous uniform distribution. This last assumption means that the stocks have monthly idiosyncratic volatilities ranging from 5% to 10%. In a typical iteration, the mean return to all stocks over the 660 month sample period is 1%, but this ranges from -3% to 6% for different stocks. Stock volatilities range between 5% to 30% with a mean of 12%.

The second economy, **FMOM+RMOM**, exhibits both factor and firm-specific momentums. The firm-specific component of this economy has a first-order autocorrelation of 0.02 and has the same volatility as the previous economy. In the third economy, **FMOM+BAB**, factors are autocorrelated, firm-specific returns are IID, and security factor lines are time-varying, but they are on average flat. We introduce time-varying SFL flatness by adding $\eta_t(1 - \overline{\beta_i}))$ every month to each stock returns. This means that, if, for example, η equals 1 in a month then the SFL for the average factor in that month is exactly flat.[13] We draw η_t from a normal distribution $\eta \sim N(1, 2)$; therefore, although SFLs are flat over the total sample, they are sometimes intact (η can be close to zero, for example, during "FOMC announcements" of Lucca and Moench (2015)), downward sloping ($\eta > 0$), or too steep ($\eta < 0$). Mean and volatility for the average stock in the second economy are very similar to the previous economies. The only difference is that the high beta and low betas assets of this economy earn similar unconditional returns.

Our last economy, **FMOM+RMOM+BAB**, contains factor momentum, firm-specific momentum, and flat SFLs. The returns are the sum of the systematic component, the RMOM component of the second economy and the BAB component of the third economy. The average stock in this economy earns an average monthly premium of 1% at a standard deviation of about 12% similar to the other three economies.

The values for the baseline parameters are chosen to produce moments similar to those of the U.S. data but the main conclusions from simulations are insensitive to the precise values of

[13]Notice that each factor earns a premium of 0.2 and the average beta is 1. With five factors, an η of 1 makes the average SFL fully flat, and an η of 2 makes SFLs downward sloping.

these parameters. For example, a lower η makes the **FMOM+BAB** economy more similar to the **FMOM** economy but it still replicates the distrorted SFL patterns found in actual data. A lower (or higher) factor autocorrelation makes all momentum strategies less (more) profitable. We are mostly interested in the differences in the behavior of momentums *across* these economies rather than the precise values we find for, for example, residual momentum profits.

We assume that our investor observes the true factor returns as well as the returns to each stock. This could mean that our trader obtains stock data from the CRSP dataset and factor data from Ken French data library and then runs regressions to estimate residuals. The trader uses past returns or past estimated residuals to form high-minus-low portfolios. The first residual momentum strategy, like the CAPM residual momentum, uses residuals with respect to the first factor. This trader falsely assumes that the systematic returns stemming from exposure to the remaining four factors are residuals. The second residual momentum strategy uses residuals with respect to three factors (i.e., FF3 residual momentum). The last strategy observes the true model and computes residuals with respect to all five factors, analogous to the FF5 residual momentum if we believe that FF5 model fully describes the systematic variation in asset returns.

The trader estimates rolling regressions with 60 months of data and then takes the most recent residual as the sort variable to target the first-order autocorrelation in firm-specific returns. The trader estimates the long-run intercept of each stock using a total sample regression.[14] All the strategies are constructed using the linear-weight scheme where allocation to each stock equals its past return or residual returns. We simulate each economy 1000 times to construct momentum, residual momentum, and intercept residual momentum strategies in each iteration. The intercept

[14]The results remain the same if use the intercept of the 60 month regression as the long-run intercept. This is because our stock betas are constant over the sample period.

residual momentum strategies are constructed using the four-step procedure of Section 4.

5.2 Result 1: The significance of the residual momentum returns or alphas is indicative of neither the absence or presence of firm-specific momentum

The left column in Figure 1 shows the distribution of t-values to returns of each strategy for each economy. We show the distribution of t-values of momentum returns in red, and those of residual momentum in blue. Residual momentum net of more factors are displayed in lighter colors. That is, the dark blue shows the t-values of the one-factor residual momentum, and the semi-light and light blue show the t-values for the three-factor and five-factor model residual momentums, respectively. The dashed lines show the critical value for significance at the 5% level (t-value = 2.00).

A sort on past returns, illustrated in red distributions, earns comparable and large t-values across all economies. The profits to the residual momentum strategies drop as we control for more factors but the speed of decline is higher in the first and third economies that do not display residual autocorrelation. The figure shows that the one factor and three factors residual momentum strategies of the **FMOM** and **FMOM+BAB** economies, that do not exhibit firm-specific momentum, are statistically significant because these residual strategies inevitably bet on factor momentum in the omitted factors. In summary, mean returns to momentum or residual momentum strategies do not reveal much about the underlying price process. They can be significant because the price process contains residual autocorrelation or because the model is incomplete.

The right column of Figure 1 shows the distribution of t-values for intercepts from the regressions of total return momentum or residual momentum on the five factors. We can compare the pattern in these distributions to those of Table 1. The residual momentum alphas of the **FMOM** economy (similar to its means) drop sharply as we hedge out more factors, reaching zero for the residual momentum net of all factors. This result is inconsistent with those of Table 1 wherein residual momentum intercepts gets boosted by the factor model.

The intercepts of residual momentums in all other economies never become completely insignificant. For the second economy, **FMOM+RMOM**, the intercept of the five factor residual momentum reflect the true alpha of momentum in firm-specific returns. However, because SFLs are not distorted, the residual momentum intercepts of this economy do not get boosted as they do in data.

There is no firm-specific momentum in the third economy (**FMOM+BAB**) as reflected in the zero mean to its five factor residual momentum. However, because SFLs are flat, a sort on residuals is also a sort against betas.[15] Therefore, controlling for the factors boosts the intercepts positively. Residual momentum intercepts are largest in the last economy (**FMOM+RMOM+BAB**) because they are a bet on the true firm-specific momentum and they contain the boosting beta bets.

To summarize, the significance of residual momentum means or intercepts does not reveal much about the price process. Residual momentum returns and intercepts can be significant because of momentum in the true firm-specific component, because SFLs are flat, because some of the factors are missing, or a combination of these effects. However, the residual momentums of the first two economies, **FMOM** and **FMOM+RMOM**, do not get boosted in factor model regressions. We can therefore dismiss the processes of (18) and (19) with high confidence. The following simulations tackle the challenge of distinguishing between the process in (20) and (21) by studying the changes to residual momentums after their beta bets are removed.

[15] The five-factor residual momentum of this economy loads negatively on the five factors with an average t-value of -3.23, comparable to the mean t-value of factor loadings in FF5 residual momentum of Table 1

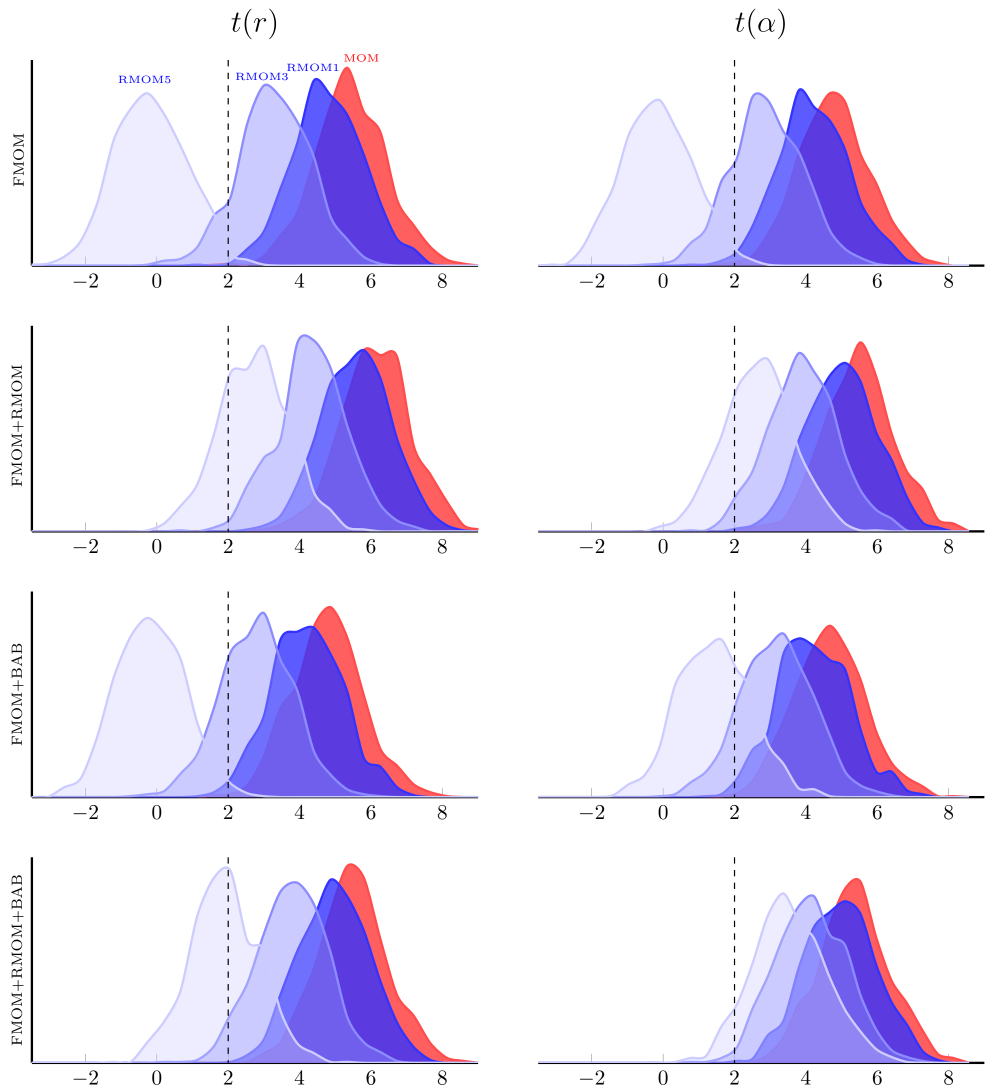

Figure 1: **Average returns and alphas of simulated momentum strategies.** This figure shows the distribution of t-values associated with mean returns of momentum (show in red) and three residual momentum strategies net of one, three, or five factors (blue). The distribution of strategies net of a larger number of factors are displayed with lighter color.

5.3 Result 2: Increase in the Sharpe ratio from removing residual momentum strategy's beta bets supports the presence of firm-specific momentum

If returns are governed by the process in (20) or (21), strategies that trade momentum based on estimated residuals will contain bets against betas. Does removing beta bets from residuals impact the residual momentum strategies of economies in (20) and (21) differently? Returns to residual momentum in (20) stem from missing factor momentum while returns to residual momentum of economy in (21) could be either missing factor momentum or firm-specific momentum.

As we show in the following this test is essential in ruling out one process in favor of the other. Therefore, before presenting the simulation results, we first confirm that the result that the U.S. iRMOM earns more than 100% higher Sharpe ratio than the standard RMOM (Table 4) is consistent across all markets. We repeat the four-step procedure of section 4 to form iRMOM in international markets. We then implement the four-step procedure on simulated data of (20) and (21) economies and put the results next to the data to learn about the price process.

Table 6 shows the mean returns to each region's RMOM and iRMOM side by side. Neutralizing intercepts bets *reduces* mean and Sharpe ratio of the CAPM residual momentums. The CAPM RMOM of Asia Pacific, for example, earns a return of 0.79% with a t-value of 3.57.[16] The CAPM iRMOM of Asia Pacific earns 10 bps lower mean (0.69%) at a slightly higher Sharpe ratio.[17] Part of the momentum in CAPM residuals is due to the momentum in the discovered factors such as SMB, HML, RMW, and CMA. A conclusion from the result that neutralizing intercepts does not improve CAPM residual momentum is that the procedure does not improve an incomplete residual momentum. We will comment on this important result with simulations.

[16] Dividing the t-values by $\sqrt{\frac{328}{12}} = 5.22$ gives annualized Sharpe ratios.

[17] Japan is an exception where neither RMOM momentum nor iRMOM earn significant returns.

Table 6: Residual Momentum and Beta-Neutral Residual Momentum in International Markets

This table reports average returns for residual momentum (RMOM) and beta-neutral residual momentum (iRMOM) strategies for Asia Pacific (AP), Europe, Japan, and North America (NA). We report t-values in parenthesis.

	CAPM		FF3		FF5	
	RMOM	iRMOM	RMOM	iRMOM	RMOM	iRMOM
AP	0.79	0.69	0.92	0.80	0.84	0.83
	(3.57)	(3.66)	(4.38)	(4.53)	(4.21)	(5.90)
Europe	0.93	0.76	0.74	0.62	0.70	0.60
	(4.83)	(4.34)	(4.55)	(4.55)	(4.95)	(5.28)
Japan	0.19	0.30	0.03	0.11	0.00	0.12
	(0.80)	(1.56)	(0.15)	(0.77)	(0.01)	(1.05)
NA	0.45	0.37	0.41	0.33	0.34	0.29
	(1.77)	(1.73)	(1.85)	(2.11)	(1.55)	(2.08)

The Sharpe ratios of FF3 iRMOMs are slightly larger than their RMOM versions. That of Asia Pacific is larger by about 5%, Europe is about the same, and NA is larger by more than 10%. Once again, the improvements are gained through the volatility channel because mean returns to iRMOMs are actually smaller than those of RMOM. Although the efficiency improvements are somewhat larger compared to the CAPM they are still subtle.

Removing intercepts increases Sharpe ratios of FF5 residual momentums the most. In doing so, the Sharpe ratio of AP's RMOM increases by 40%, that of Europe increases by 7%, and that of NA increases by 34%. Moreover, unlike the iRMOM of less extended models that earn lower means than their RMOMs, mean returns of FF5 iRMOMs are about the same as those of the FF5 RMOMs. We next turn into simulations to test how the moments of RMOM and iRMOM compare in economies that have flat SFLs but differ in having or not having firm-specific autocorrelation.

Figure 2 shows the percent change in mean, volatility, and Sharpe ratio of residual momentums of our two candidate economies as a result of beta-neutralizing the residuals. RMOM1 is the residual momentum net of the first factor (leaving four factors out in the residuals), RMOM2 is the residual momentum net of the two factors, and so on until RMOM5, that is the residual momentum net of all five factors. ΔRMOM measures by how much a moment of a residual momentum changes when its bets bets are removed. That is, for example, we compute ΔRMOM1=(iRMOM1−RMOM1)/RMOM1 for mean, standard deviation, and Sharpe ratio to learn how each moment of the first residual momentum changes when its beta bets are expunged. Our focus is not on the magnitude of changes, rather we are interested in finding where the two economies diverge and if so, which fits the data better.

In the **FMOM+BAB** economy there is no firm-specific momentum hence residual momentum returns are only a reflection of missing factor momentum. The top left panel shows that removing intercept bets reduces the mean returns to residual momentums of **FMOM+BAB** but the magnitude of the decline gets smaller for the residual momentums net of more factors. Mean returns for the economy with firm-specific momentum (**FMOM+BAB+RMOM**) exhibit a similar pattern except for the last portfolio. This result means that if returns really contain firm-specific momentum, and if we identify all the true factors, then removing intercepts from residuals may increase mean returns to the residual momentum strategy.

The theoretical explanation to this observation, that removing intercept bets of incomplete residual momentum strategies reduces their means, was provided in Section 3.2: to remove the beta bets we have to change the portfolio's asset weights such that it becomes orthogonal to factor betas. Any rotation in asset allocations inevitably weakens factor momentum by reducing $\sigma^2_{\beta_f}$ in equation (16).

The second row shows that standard deviations drop across the board because neutralizing intercepts removes the volatility stemming from the time-varying slopes of SFLs. The decline in volatility is larger for the extended residual momentums. To sum the results for changes in mean and standard deviations, we find that both moments are smaller for simulated iRMOMs compared to RMOM. This behavior is fully consistent with the empirical results in Table 6: all international iRMOMs have a lower mean and standard deviation than their RMOM counterparts. Therefore, the changes in the first two moments by themselves do not help us distinguish between the two return process candidates.

The third row shows the impact of removing intercept bets of RMOM on Sharpe ratios of the strategy. Sharpe ratios of all residual momentum strategies on the left (the **FMOM+BAB** economy) decline. In contrast, the columns on right show that Sharpe ratios increase for the economy that contains firm-specific autocorrelation. Moreover, increases are larger when residuals are computed net of more factors. The divergence between the two economies indicates that the only component of residual momentum that can benefit from removing the intercept bets of residuals is the firm-specific component. Missing factor momentum, which is the source of residual momentum profits in FMOM+BAB, can only get weaker. These results reinforce the conjecture that constructing iRMOM instead of RMOM is more mean-variance efficient only when the process contains firm-specific autocorrelation.

The changes in Sharpe ratios of empirical residual momentums of Table 6 are only consistent the **FMOM+BAB+RMOM** economy. Table 6 shows that Sharpe ratios remain the same for the CAPM iRMOM (relative to CAPM RMOM), increase modestly for the FF3 iRMOM (relative to FF3 RMOM), and increase substantially for FF5 iRMOM (relative to FF5 RMOM). This result is precisely what simulations forecast for the **FMOM+BAB+RMOM** economy. We have repeated these simulations with different number of factors and different parameter values. In every test,

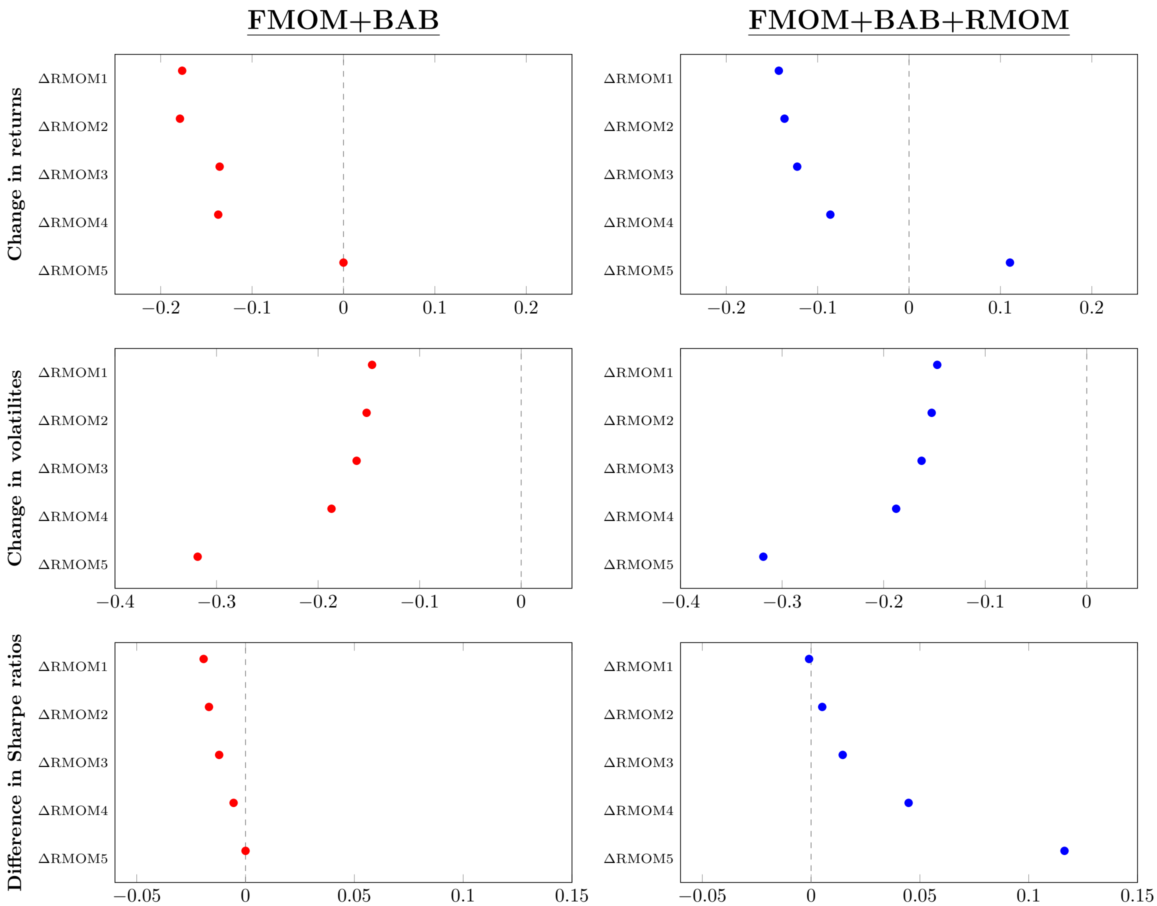

Figure 2: **Changes in the moments of the simulated residual momentum strategies.** This figure shows the changes in mean, standard deviation, and Sharpe ratio of five residual momentum strategies as a result of removing their bets bets.

we find that the Sharpe ratios for RMOMs of **FMOM+BAB** economy suffer while those of the **FMOM+BAB+RMOM** economy benefit from neutralizing the intercept bets.

5.4 Result 3: Lack of covariation between global beta-neutral residual momentum strategies is evidence of firm-specific momentum

International momentum strategies are correlated. If international asset returns obey a process such as the one in (21), the covariation between residual momentum strategies of two different regions could be due to the covariation between their missing factor momentums, covariation between their time varying flatness in their SFLs, or covariation between their firm-specific momentums. It is common knowledge that international factors are autocorrelated and so is the momentum in their factors. Moreover, Ehsani and Linnainmaa (2022) show that the flatness in the average security market line of different markets are highly correlated. They find that portfolios sorted on intercepts of different international markets show the largest covariation of all cross-sectional factors. The true firm-specific return is the only component that is uncorrelated by definition. Strategies that trades momentum using true firm-specific returns can only be correlated if a common component such as sentiment drives the *autocorrelation* in firm-specific returns of different regions.

The three aforementioned sources can be responsible for the covariation between different residual momentums. Therefore, the presence of covariation between different residual momentums is not insightful while its absent is a strong sign of momentum in the firm-specific component. For example, suppose that removing intercept bets of residual momentum strategies reduces their co-movement. This result supports both of these statements: 1) the iRMOMs are more firm-specific and 2) firm-specific momentum does not have a common component. Notice that factor momentum and SFLs can only generate covariation; any drop in comovement is a sign that the strategies are less systematic and, therefore, more firm-specific.

An empiricist that observes the complete set of factors and is aware that SFLs are flat can extract the firm-specific component by following the four-step procedure introduced in the earlier section. In absence of a common driver for firm-specific autocorrelation in different regions, iRMOM of different markets should be uncorrelated. Panel A of Table 7 shows the pairwise correlations between residual momentum strategies of different regions. The CAPM RMOMs are highly correlated, with correlations ranging between 0.30 (between Asia Pacific and Japan) and 0.65 (between Europe and North America). The FF3 and FF5 RMOMs of different regions are also highly correlated. The pairwise correlations between iRMOMs are always smaller, indicating that removing intercepts reduces the comovement between residual momentums of different regions.

Panel B of Table 7 reports the average correlations for each model across all regions with their 95% confidence intervals. The average pairwise correlations between CAPM RMOMs across all regions is 0.45. Residual momentums formed using FF3 and FF5 are also very highly correlated with mean correlations of 0.42 and 0.40, respectively. The result that residual momentums formed using FF3 and FF5 are as correlated as those formed using CAPM gives the impression that different firm-specific momentum strategies are highly correlated.

The mean correlation between CAPM iRMOMs is 0.37 compared to 0.45 for the CAPM RMOM strategies. The decline of 0.08 is statistically significant. Neutralizing intercepts of FF3 and FF5 residuals reduces the pairwise correlation between the strategies even more: the average correlation between FF3 iRMOM is 0.12 smaller than FF3 RMOM, and the average correlation between FF5 iRMOM is 0.16 smaller than FF5 RMOM. These results indicate that neutralizing intercepts is more effective in reducing commonality of the more extended RMOMs. Still, the mean correlation between FF5 iRMOMs is 0.24 and statistically significant which suggests that some common components remain in the returns to the strategies. Nonetheless, the smaller covariation between iRMOMs is direct evidence that these portfolios are more firm-specific compared to the original RMOMs. The remaining comovement can be a sign of missing factors or a common component in

Table 7: Comovement Among International Residual Momentum Strategies

Table reports correlation between residual momentum strategies (RMOM) and beta-neutral residual momentum strategies (iRMOM) in international markets.

Panel A. Pairwise correlation between different regions						
	Model: CAPM		Model: FF3		Model: FF5	
	RMOM	iRMOM	RMOM	iRMOM	RMOM	iRMOM
AP & EU	0.45	0.33	0.41	0.24	0.34	0.13
AP & JPN	0.30	0.18	0.31	0.14	0.34	0.19
AP & NA	0.46	0.26	0.38	0.18	0.34	0.13
EU & JPN	0.40	0.38	0.35	0.33	0.35	0.31
EU & NA	0.65	0.66	0.62	0.58	0.59	0.42
JPN & NA	0.45	0.41	0.45	0.32	0.42	0.26
Panel B. Average correlations						
	Model: CAPM		Model: FF3		Model: FF5	
	Mean	95% CI	Mean	95% CI	Mean	95% CI
RMOM	0.45	[0.36–0.53]	0.42	[0.33–0.50]	0.40	[0.31–0.48]
iRMOM	0.37	[0.28–0.46]	0.30	[0.22–0.37]	0.24	[0.18–0.30]
Difference	0.08	[0.02–0.15]	0.12	[0.04–0.21]	0.16	[0.07–0.25]

the autocorrelation in the firm-specific component.[18]

5.5 Result 4: Lack of covariation between beta-neutral residual momentum and factor momentum supports the existence of firm-specific momentum

Table 8 shows the correlation between different definitions of residual momentum and two definition of factor momentum for the U.S. data. The first column shows the correlation between residual momentum and the factor momentum of Ehsani and Linnainmaa (2020). The CAPM residual momentum covaries strongly with factor momentum ($\rho_1 = 0.55$). The FF5 residual momentums

[18] In unreported simulations for the **FMOM+RMOM+BAB** economy, where the commonality in iRMOMs can only derive from missing factor momentum or flatness in betas, we find that the changes between iRMOM correlations follow the same pattern of Table 7. For example, we find that removing intercept bets does not reduce the correlations between residual momentums net of one or three factors. The large comovement in beta-neutral residuals momentums net of few factors, that is is due to the comovement in their missing factor momentum, indicates that the comovement from missing factor momentum overwhelms the drop in comovement as a result of removing the BABs. Removing BABs is highly effective in reducing residual momentum comovement for the complete residual momentum or an incomplete residual momentum that misses just one factor.

Table 8: Correlations Between Residual Momentum and Factor Momentum

This table shows the correlation between residual momentum and factor momentum. The number of observations is 672. The coefficient t-values equal $\frac{\rho\times\sqrt{672-2}}{\sqrt{1-\rho^2}}$, where ρ is the correlation coefficient. The last column uses Fisher (1915) z-transformation test for the null of $\rho_1 = \rho_2$.

Correlation between FMOM &	ρ_1	Correlation between FMOM &	ρ_2	$H0 : \rho_1 = \rho_2$ z−value
$\text{RMOM}_{\text{CAPM}}$	0.55	$\text{iRMOM}_{\text{CAPM}}$	0.39	(−3.71)
RMOM_{FF3}	0.42	$\text{iRMOM}_{\text{FF3}}$	0.20	(−4.35)
RMOM_{FF5}	0.36	$\text{iRMOM}_{\text{FF5}}$	0.19	(−3.34)

covaries less with factor momentum yet the correlation of 0.36 is still large. The next column shows that factor momentum covaries far less with iRMOMs. The correlation between factor momentum and the FF5 iRMOM is 0.19, and the decline of 0.17 units (from 0.36 to 0.19) is statistically significant with a z-value of −3.34.

6 Which mechanism generates equity momentum?

Our results shed light on rational and behavioral theoretical models of momentum. Rational theories argue that momentum is the result of prior returns influencing expectations about the future performance and riskiness of the underlying stock. Behavioral models argue that momentum stems due to psychological biases or gradual diffusion of information in financial markets. These models make distinct forecasts about the pattern in realized returns. We estimate the predictability of factor returns and firm-specific returns from prior returns as a criterion to assess the models.

Figure 3 presents the autocorrelation in 22 off-the-shelf factors from Ehsani and Linnainmaa (2020). We report the t-values from pooled regressions of factors on their lagged values. Figure 4 shows the t-values from Fama and MacBeth (1973) regressions of beta-neutral residuals on their lagged values. The most notable discrepancy is autocorrelation at the first lag: factor returns are the most persistent at this lag (t-value of 2.8) while firm-specific returns show enormous reversal (t-value of -10).[19] Factors and firm-specific returns exhibit alike autocorrelation patterns between lags two and 12 after which the figures once again diverge. Beyond the 12th lag, factors display a mix of positive and negative autocorrelation while firm-specific returns display a significant reversal. We conclude that the short-term and long-run reversal effects are purely firm-specific whereas the intermediate momentum effect is created by both effects. The distinct patterns in autocorrelations implies that these effects are likely generated by unrelated mechanisms. In the following we provide a summary for the models and relate their forecasts to the empirical patterns in factor and firm-specific returns.

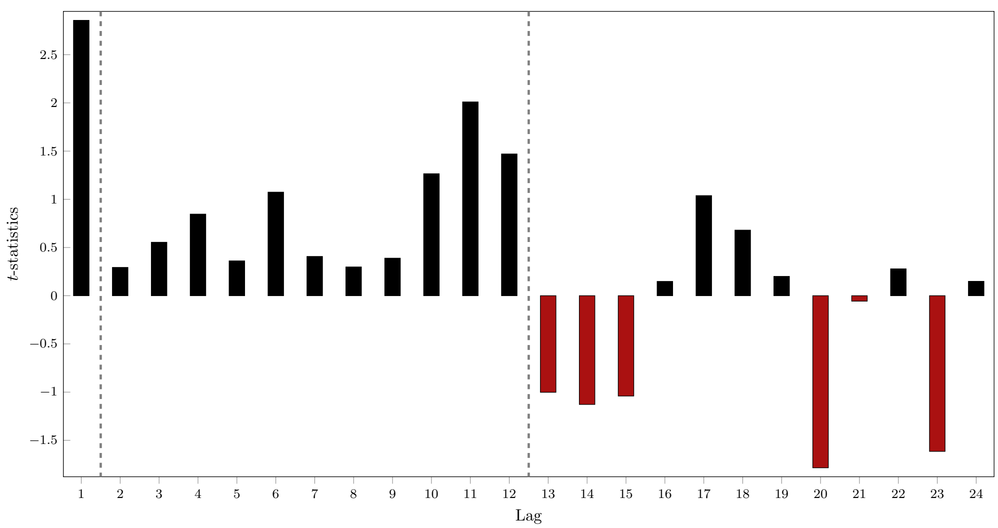

Figure 3: **Autocorrelation in factors returns.**

Berk, Green, and Naik (1999) provide a rational model of momentum returns. Firms that perform well are those that have discovered valuable investment opportunities. As they exploit

[19] If instead of beta-neutral residuals, we regress the original estimated residuals on their lags, we do not find any evidence of reversal in long term returns because of the embedded beta bets. That figure would mislead the researcher to conclude that"firm-specific" returns exhibit momentum beyond at all but the first lag.

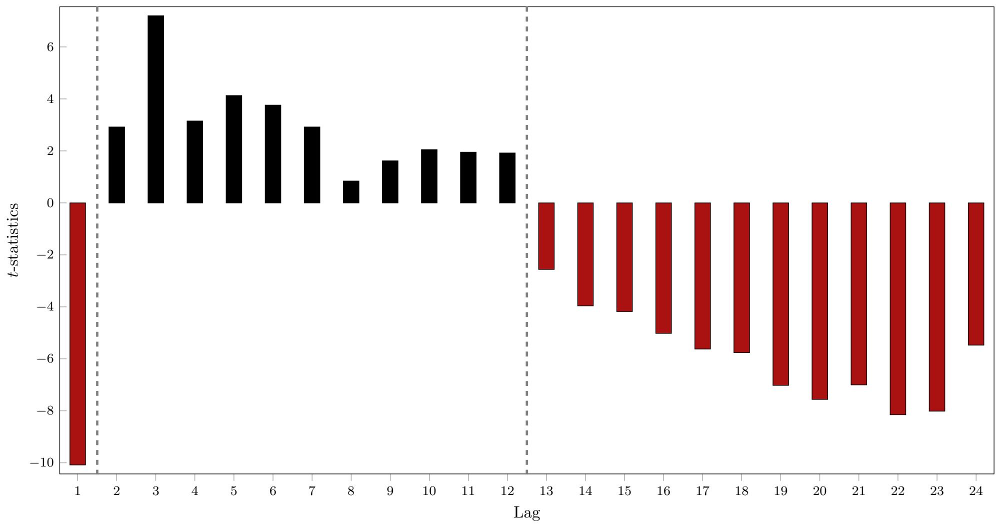

Figure 4: **Autocorrelation in firm-specific returns.**

those opportunities, their systematic risk changes. Slow turn-over in the firm's project portfolio leads to persistence in the firm's asset base and its market risk, making current expected returns positively correlated with past realized returns. Berk, Green, and Naik (1999) note that this mechanism leads to momentum at longer horizons and reversal at short horizons. In Johnson (2002), a positive relation between expected returns and firm growth rates creates momentum in a firm's value. Johnson argues that growth rate risk rises with growth rates. If exposure to this risk is compensated, expected returns rise with growth rates. All else equal, firms that recently experienced positive price moves are more likely to have positive growth rate shocks. Sagi and Seasholes (2007) posit that momentum stems from firm attributes. They argue that a firm's (high) revenues volatility, (low) costs of goods sold, and (high) book-to-market combine to determine the dynamics of its return autocorrelation. Ehsani and Linnainmaa (2020) builds on Kozak, Nagel, and Santosh (2018) model of sentiment to show that the extent to which factors show reversal or momentum depends on the persistence of sentiment-driven demand that aligns with covariances. If sentiment is sufficiently persistent, factors exhibit momentum. Although arbitrageurs know that factor premiums are predictable, they do not trade sufficiently aggressively to neutralize this effect because, in doing so, they would expose themselves to factor risk. This model predicts that momentum should concentrate in more systematic factors. These models are not excellent explanations of firm-specific momentum because they explain momentum through a systematic mechanism.

Behavioral models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) argue that momentum stems due to psychological biases or gradual diffusion of information in financial markets. Daniel, Hirshleifer, and Subrahmanyam (1998) argue that "self-attribution bias", that investors attribute success to their own skill (more than they should) and attribute failure to external noise (more than they should), is the source of return momentum. Therefore, the momentum in Daniel, Hirshleifer, and Subrahmanyam (1998) is a reflection of investor overreaction which, in the long-run, reverses as investors observe new information and adjust their beliefs. The agents in Hong and Stein (1999), on the other hand, are subject to initial underreaction and subsequent overreaction: "newswatchers" rely exclusively on their private information whereas "momentum traders" rely on past price information. A critical assumption in Hong and Stein is that private information diffuses gradually through the marketplace, creating an initial underreaction to news followed by positive serial correlation in returns. Momentum traders observe the underreaction pattern of newswatchers and their trading activity eventually leads to overreaction to news. The momentum and reversal in Vayanos and Woolley (2013) derive from flows between investment funds. Investors observe or infer fund managers' skill from past performance and adjust the fund flows. Momentum arises because flows adjust slowly and because rational prices underreact to expected future flows.

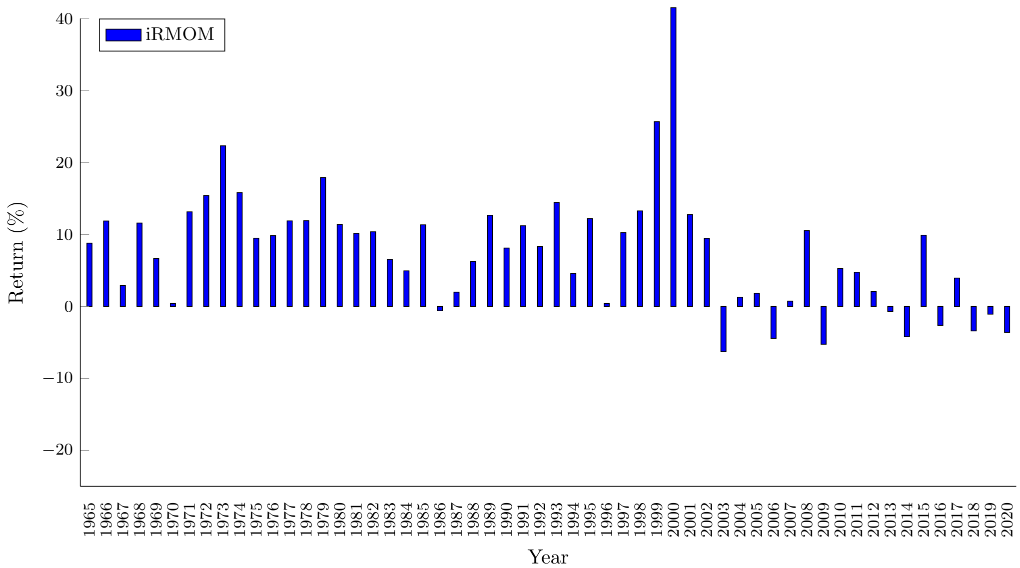

Figure 5: **Historical returns to beta-neutral residual momentum.** This figure shows the annual returns to the beta-neutral residual momentum (iRMOM) strategy.

Based on our empirical results, namely, the small covariation between different firm-specific momentum strategies and the small covariation between firm-specific and factor momentum, a behavioral explanation of firm-specific momentum is more appropriate. The pattern in firm-specific autocorrelations of Figure 4, an initial overreaction succeeded by a sharp reversal, appears most consistent with a theory of investor bias such as the self-attribution of Daniel, Hirshleifer, and Subrahmanyam (1998).

These properties give firm-specific momentum the status of a near-arbitrage strategy—high Sharpe ratio and low correlation with systematic risk. Theory predicts that such opportunities should disappear as traders learn from the data. Indeed, the decline in firm-specific momentum profits is evident in Figure 5. Between 1965 and 2000, iRMOM earns an average annual return of 10.10% (t-value of 10.48) whereas in post-2000 data the returns become 3.45% (t-value of 1.53). Firm-specific momentum profits declined as arbitrageurs learned about the strategy.

7 Conclusions

Momentum is present in most asset classes and, in some cases, going back hundreds of years (Geczy and Samonov 2016; Goetzmann and Huang 2018). Because of its economic magnitude and breadth, questions about the sources of momentum profits remain of intense interest. Do past winners tend to outperform past losers because winners and losers are mispriced—or because of differences in systematic risk? The finding that residual momentum strategies are more profitable than total momentum strategies seems to provide a tantalizing clue: if momentum resides, at least in part, in firm-specific returns, does not it imply that at least this share of momentum must be about mispricing?

The problem with the argument that momentum resides in firm-specific returns is that winners and losers behave *as if* they are exposed to the same sources of risk. Cochrane (2011, p. 1075), for example, wonders "...why should all the momentum stocks then rise and fall together the next month, just as if they are exposed to a pervasive, systematic risk?" Ehsani and Linnainmaa (2020) show that factors, too, display momentum; that this momentum transmits into the cross section of stocks; and that factor momentum explains much or all of individual stock momentum. Although this result answers Cochrane's question, it does not, however, preclude the possibility that there is momentum also in firm-specific returns.

In this paper we show that residual momentum strategies confound three distinct effects: momentum in firm-specific returns, bets against betas, and momentum in factors omitted from the asset pricing model. The finding that residual returns display more momentum than total returns therefore provides inconclusive evidence about momentum in firm-specific returns. Although it could signify that there is momentum in firm-specific returns, it could also indicate that the security factor lines are flat (which they are) or that some factors outside the Fama-French also display momentum (which they do).

We show that the statistical behavior of residual momentum strategies alone—the way the alphas, the loadings, and the R^2 statistics change—indicates that the flatness of the security factor lines significantly contribute to their profits. We then propose a method for removing this betting-against-beta effect from the residuals. Our method builds on the idea that while momentum is a short-term effect, betas are not. We estimate short-term residual returns and long-term betas, selecting a lookback window over which returns display neither momentum nor reversals, and orthogonalize one against the other. The resulting adjusted short-term residuals no longer have the beta bets. This process significantly reduces the volatility of the residual momentum strategy and, consequently, its Sharpe ratio increases from 0.59 to 1.23.

The increase in the residual momentum strategy's mean-variance efficiency still does not prove that firm-specific returns display momentum. The remaining alpha could emanate from factors omitted from the asset pricing model. Perhaps, by removing some factors and the beta betas, the momentum present in the omitted factors leaves an even stronger mark in the residuals. We show that this explanation is unlikely. The beta-neutral residual momentum strategies are more firm-specific and less factor-like than the original residual momentum strategies: they correlate less with each other across regions and they correlate less with Ehsani and Linnainmaa's (2020) factor momentum.

Our findings support behavioral theories of momentum: most of the profits that we deem as being about firm-specific momentum dissipate as the holding period lengthens. This pattern, which is absent from the factor momentum component, is fully consistent with the behavioral theories, such as that in Daniel, Hirshleifer, and Subrahmanyam (1998), that prescribe momentum to an interplay between under- and overreaction. If so, our results might appear to leave open a large question in the form of near-arbitrage profits: if momentum is about firm-specific returns and the Sharpe ratio associated with beta-neutral residual momentum is so high, how can this effect persist? We show that it apparently does not: almost all of the outsized returns accrued before 2002. As arbitrageurs learned about and began to trade momentum, much of the firm-specific momentum vanished.

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