How Much of Cross-Stock Momentum Reflects Underreaction? *

Jiacui Li and Jingda Yan

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ABSTRACT

Numerous studies document cross-stock momentum — situations where returns of related stocks cross-predict each other — and interpret these patterns as underreaction to cash flow information. However, we find that these returns revert over the long run, which is hard to reconcile as underreaction. Our further examination reveals that existing findings on cross-stock momentum are not limited to unidirectional lead-lag relationships from the peer firms to focal firms; instead, they inadvertently incorporate common movements among these stocks. Notably, those common components exhibit short-run momentum followed by long-run reversals. After removing these common components, the residual cross-stock momentum aligns more closely with the underreaction hypothesis: returns do not revert and are stronger in stocks with higher arbitrage costs. Our estimates indicate that unidirectional lead-lags account for approximately one-third of the previously documented cross-stock momentum returns.

JEL classification: G11, G12, G14

Keywords: Lead-Lag, Cross-Stock Momentum, Factor Momentum, Reversal, Underreaction

*Li (jiacui.li@eccles.utah.edu) is at David Eccles School of Business, University of Utah. Yan (yanjingda@rmbs.ruc.edu.cn) is at Finance at School of Business, Renmin University. We are grateful to comments from Aaron Burt, Aditya Chaudhry, David Hirshleifer, Christopher Hrdlicka, Allen Hu, Stephen Teng Sun, and presentation participants at Fudan School of Management, Monash Business School, NYU Shanghai, University of Queensland, and Utah. We thank Thummim Cho and Andrea Tamoni for sharing data.

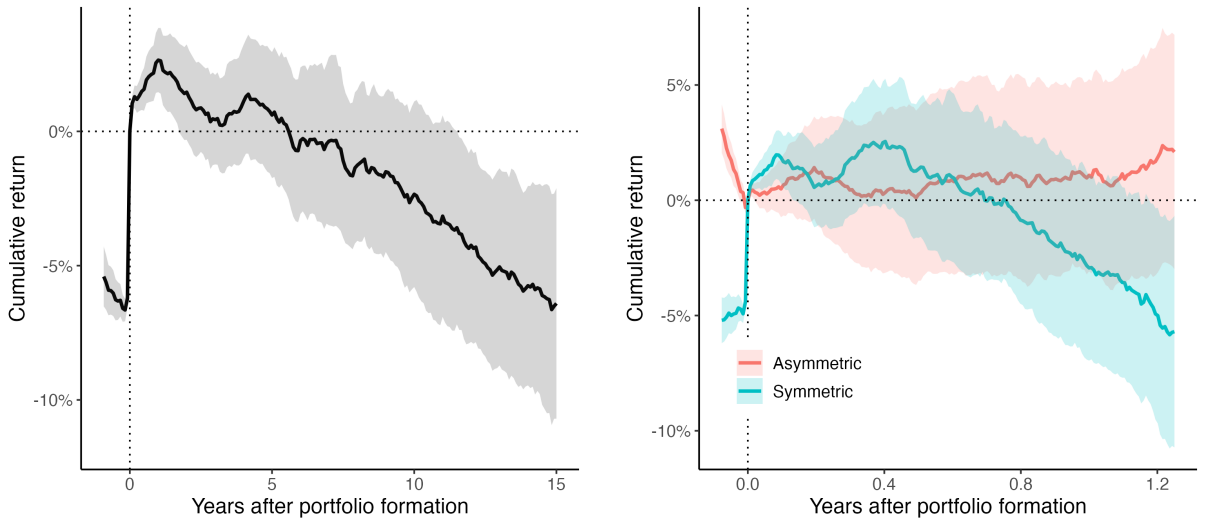
1 Introduction

A long literature has documented cross-stock momentum patterns whereby the returns of peer stocks predict that of other related focal stocks. For instance, Cohen and Frazzini (2008) find that the stock returns of customers firms lead the suppliers. Relatedly, researchers also find lead-lag patterns among stocks in the same industry (Moskowitz and Grinblatt, 1999), in the same geographic area (Parsons et al., 2020), with technology links (Lee et al., 2019), with overlapping analyst coverage (Ali and Hirshleifer, 2020), and so on. These findings have been interpreted as underreaction to cash flow information. Based on this interpretation, several papers further interpret such as reflecting investor inattention or market segmentation (e.g. Menzly and Ozbas, 2010).

In this paper, we document that these return patterns revert in the long run, which is hard to reconcile with the undereaction interpretation. In fact, the eventual reversal is larger than the initial returns, suggesting that cross-stock momentum represents moving further away from, rather than resolving towards, long-run equilibrium price levels. To shed light on the source of reversals, we demonstrate that a significant component of cross-stock momentum reflects common factor momentum between the peer and focal stocks, rather than uni-directional leag-lag relationships. The former component explains around two-thirds of the initial momentum and all of the reversals. The latter component, which accounts for around one-third of the initial momentum, is more consistent with the traditional underreaction explanation.

Our empirical work starts by demonstrating long-run return reversals. We replicate nine prominent cross-stock return predictors and find that their initial returns invariable reverse over the next five to ten years. For simplicity of exposition, we illustrate the key findings in Panel (a) of Figure 1 using a combined predictor that averages the information over those nine predictors. We plot the cumulative returns of the value-weighted long-short decile portfolio formed using this combined predictor. Consistent with the previous literature, this portfolio

indeed exhibits high returns within twelve months of portfolio formation. However, the return reverts subsequently. In return forecasting regressions, the point estimate indicates full reversal after approximately five years. We demonstrate most of our findings using this combined predictor, but the result is robust across all predictors and over subperiods.



(a) Cross-stock momentum

(b) Decomposed cross-stock momentum

Figure 1. Post-portfolio formation return of cross-stock momentum.

We study the cumulative return of long-short value-weighted NYSE decile portfolios sorted on cross-stock momentum predictors. The sorting variable, described in section 2.1, is the average value across individual cross-stock momentum predictors. Panel (a) plots the cumulative returns over the subsequent 15 years. Panel (b) further decomposes the predictor into a symmetric component that can be understood as reflecting factor momentum and an asymmetric component that reflects unidirectional lead-lag relationships. The decomposition is described in Section 3. For both panels, shaded areas are 95% Newey-West confidence intervals.

Over a fifteen year horizon, the reversal becomes even larger than the original momentum returns, with a statistically significant difference. To the extent that prices converge towards equilibrium levels in the long run, this suggests that the original cross-stock momentum returns is a "build-up" anomaly where prices move further away from equilibrium levels (Van Binsbergen et al., 2023). As a corroboration, we examine the measure of mispricing in price levels developed by Van Binsbergen et al. (2023), and the results are consistent. That is, their measure indicates that, in the portfolio formatino period, stocks in the long

portfolios sorted by cross-stock momentum predictors are already over-priced relative to those in the short portfolios. The price deviation further exacerbates in the next twelve months before reverting back towards zero.

To better understand where the reversal comes from, we note that, perhaps contrary to common intuition, these cross-stock momentum predictors do not just reflect uni-directional lead lags from peer stock A to focal stock B. They also usually find B to lead A at the same tie, which suggests that the return patterns may arise from common return components shared by A and B, and those common components can exhibit short-run momentum and long-run reversals. To gauge this possibility, we also examine the returns for peer firms, and find that their long-horizon return patterns closely mirror that of the focal firms. The peer firms also experience short-run momentum and long-run reversals. The long-short portfolios of peer firms have correlations in the range of 50-70% with that of the focal firms, indicating that they indeed share large common components.

To separate the common component from cross-stock momentum, we follow Yan and Yu (2023) to decompose returns into a symmetric component and an asymmetric component. To explain this decomposition, note that different cross-stock momentum predictors amounts to different predictions on the $N \times N$ matrix of $\Pi = Cov(r_{t+1}, r_t')$ where r_t is the vector of stock returns. The vector of return prediction is simply $s_t = \Pi \cdot r_t$. Yan and Yu (2023) decompose the matrix into two parts:

$$\Pi = \underbrace{\frac{\Pi + \Pi'}{2}}_{\Pi_{\text{sym}}} + \underbrace{\frac{\Pi - \Pi'}{2}}_{\Pi_{\text{asy}}} \tag{1}$$

and show that the symmetric component can be interpreted as capturing momentum in common factors, whereas the asymmetric component reflects unidirectional lead-lags between stocks. We use their approach to decompose the return predictor into $s_t^{\text{sym}} = \Pi_{\text{sym}} \cdot r_t$ and $s_t^{\text{asy}} = \Pi_{\text{asy}} \cdot r_t$, and use them to construct separate long-short portfolios. We find that the

symmetric component accounts for around two-thirds of the short-run momentum returns and all of the long-run reversal, as shown in Panel (b) of Figure 1.

The asymmetric component appears more consistent with the traditional underreaction explanation. It reflects unidirectional lead lags between stocks (by construction), does not revert, and manifests most strongly in stocks that are hard to arbitrage. It explains around one-third of the initial cross-stock momentum in value-weighted portfolios. In contrast, the symmetric component is akin to the factor momentum finding in Arnott et al. (2023), and is hard to reconcile with underreaction explanations. Not only does its return revert over time, its initial returns are also almost equally strong in liquid stocks. We do not take a stance on the exact mechanism for this component, as the literature has not reached a consensus on the drivers of factor momentum, but possible explanations include overreactions in investor beliefs (e.g. Daniel et al., 1998; Barberis et al., 1998, 2015), performance chasing (e.g. Barberis and Shleifer, 2003), or persistent institutional trading pressures (e.g. Hong and Stein, 1999; Vayanos and Woolley, 2013; Sialm et al., 2015).

Our results are robust to alternative ways to control for common factor components. Burt and Hrdlicka (2021) proposes to construct the cross-stock momentum predictors using the return residuals obtained after controlling for factor exposures. If there is no uncertainty in estimating factor model loadings, we show that their method is equivalent to ours when the number of factors controlled is large enough to span the entire common component. Consistent with this, when we progressively increase the number of factors being controlled for in their methodology, the estimate of the size of unidirectional lead-lag return predictability converge towards ours.

The main contribution of this paper is a nuanced interpretation of the cross-stock momentum. We demonstrate that the conventional implementation of cross-stock momentum includes a significant common component that reverts over the long run. At an implementation level, we suggest future researchers control for the common component to isolate the uni-directional

lead lags that are more likely to reflect underreaction. As a side product, our results also indicate that factor momentum of Gupta and Kelly (2019) and Arnott et al. (2023) reverses over time.

This paper is related to Burt and Hrdlicka (2021) who are the first to point out that cross-stock momentum may reflect "commonality in momentum", a point that Yan and Yu (2023) formalize using the symmetric-asymmetric decomposition used in this paper. Our examination of long-run return patterns of cross-stock momentum is similar in spirit to the literature on stock momentum. Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) find that stock momentum reverts, which lends support to the "continued overreaction" view of momentum (e.g. Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999). Our paper is also related to the literature on factor momentum (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022a; Arnott et al., 2023), and we contribute to that literature by showing that factor momentum reverses.

2 Cross-Stock Momentum Reverses Over Time

2.1 Data and cross-stock momentum predictors

Stocks and characteristics. We obtain monthly prices and returns for U.S.-listed common stocks from CRSP. To avoid the influence of small or illiquid stocks, we filter out stocks with prices below 5 U.S. dollars per share and those with lagged market capitalization below the 20th percentile of NYSE stocks. Our sample is from 1926 to 2023. When not requiring additional variables, our sample has a total of 1,714,600 stock-month observations and an avearge of 1,458 stocks in each month. We use the stock characteristics data from Chen and Zimmermann (2022).

Cross-stock momentum predictors. We examine the eight cross-stock momentum predictors in Yan and Yu (2023) as well as the additional one from Yan and Yu (2023). Table

1 summarizes these nine predictors at the order in which they become available. The one-month industry momentum of Moskowitz and Grinblatt (1999) is available from the start of the sample. The Yan and Yu (2023) data-driven cross-stock momentum predictor is availble from 1931. In 1953, the BEA customer- and supplier-based predictors in Menzly and Ozbas (2010) become available. The list is then followed by the Technology link-based predictor of Lee et al. (2019) in 1969, the geographic link predictor of Parsons et al. (2020) in 1969, the complicated firm predictor of Cohen and Lou (2012) in 1977, the economic link predictor of Cohen and Frazzini (2008) in 1977, and the analyst co-coverage-based predictor from Ali and Hirshleifer (2020). As discussed in the introduction, most of these cross-stock predictability patterns have been interpreted as evidence of slow cash flow-information diffusion and investor inattention. In unreported tests, we verify that we can replicate the main findings of these papers closely.

To make these predictors comparable to each other, we follow a convention in the return predictability literature and transform them into uniform distributions over -0.5 to -0.5 in each cross-section (e.g. Kelly et al., 2019).

A combined predictor. To simplify exposition, in much of our empirical work, we focus on a simple combination of these nine predictors. We follow Stambaugh and Yuan (2017) to combine them by simply taking an average of all the predictors values when available. For instance, between 1953 and 1962, this combined predictor is an average between the four predictors available during that period of time: the industry momentum, data-driven, BEA-customer, and BEA-supplier predictors, respectively. For a predictor has missing values for certain stocks, we simply fill in zeros which are the cross-sectional averages. As more predictors become available over time, the number of inputs into this combined predictor also changes.

While this averaging procedure is simple, one may worry that it is not justified by portfolio choice. Therefore, we also construct another combination formed using return-predicting

Predictor	Paper	Start	Firms	Coverage	
				EW	VW
	(1)	(2)	(3)	(4)	(5)
Industry momentum	Moskowitz and Grinblatt (1999)	1926	1,325	96%	96%
Data-driven	Yan and Yu (2023)	1931	831	59%	87%
BEA customer	Menzly and Ozbas (2010)	1952	1,328	77%	77%
BEA supplier	Menzly and Ozbas (2010)	1952	1,328	77%	77%
Technology link	Lee et al. (2019)	1963	720	42%	67%
Geographic link	Parsons et al. (2020)	1969	913	46%	46%
Complicated firms	Cohen and Lou (2012)	1977	1,513	74%	77%
Economic link	Cohen and Frazzini (2008)	1978	853	40%	70%
Analyst coverage	Ali and Hirshleifer (2020)	1983	1,932	88%	92%

Table 1. Cross-stock momentum predictors.
The table lists the nine cross-stock momentum predictors from the previous literature that we replicate. We examine these predictors on stocks that are above the 20% NYSE size cutoff. Column (1) lists the original papers. Column (2) is when the predictor becomes available. Column (3) reports the average number of firms. The last two columns report the equal- and value-weighted (EW and VW) fraction of stocks covered.

multivariate regressions. The resulting "regression-combined predictor" weighs each input predictor by their relative contribution to return prediction. Appendix A.3 describes the combination procedure in detail. All our results are robust to using this alternative combination procedure. To make the combined predictors comparable to the input predictors, we also transform the combined predictors into uniform distributions over -0.5 to +0.5 in each month.

2.2 Return reversal

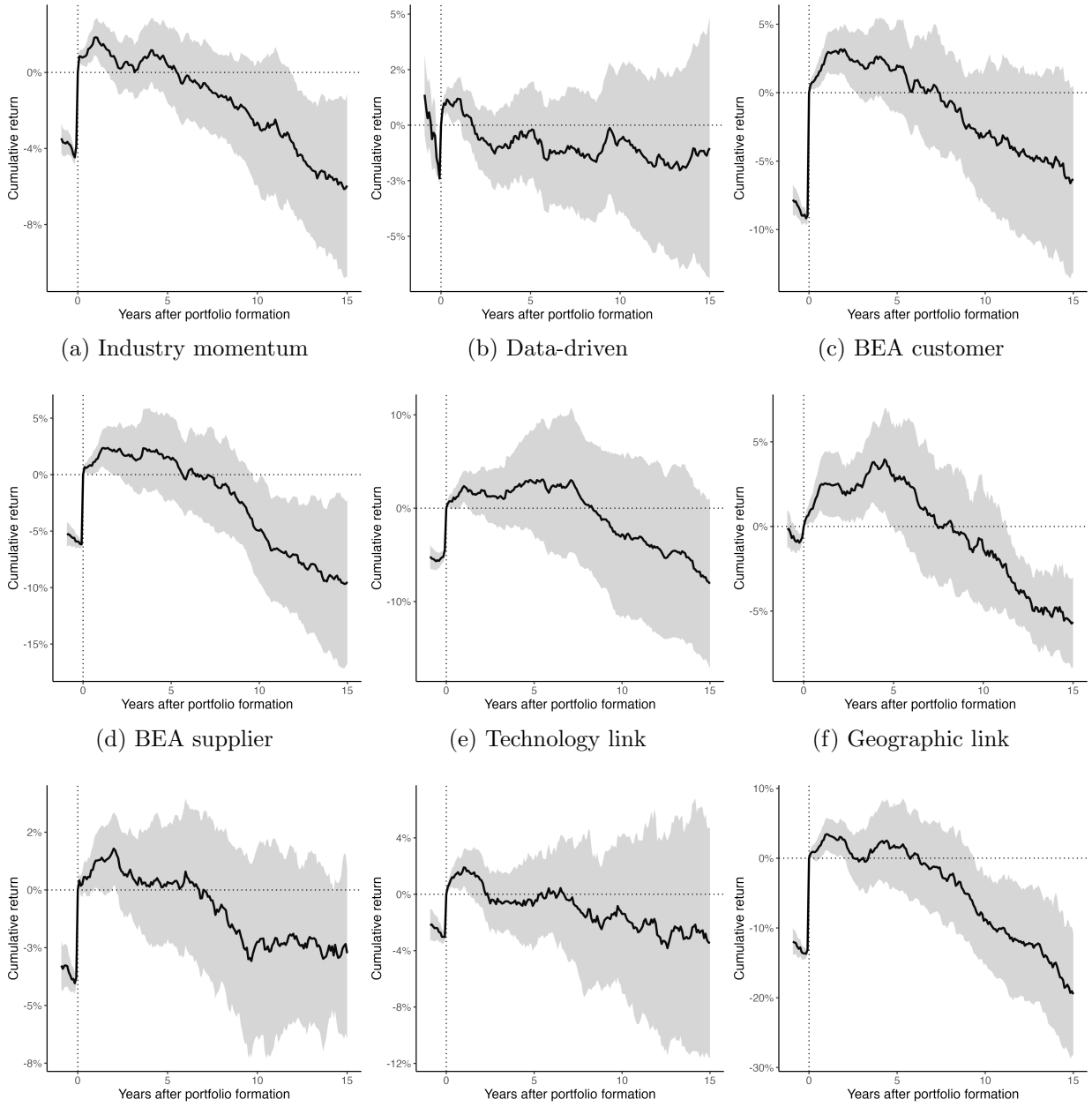
To examine long-horizon return patterns, we first sort stocks cross-sectionally into NYSE deciles based on the combined cross-stock predictor. We compute long-short decile value-weighted portfolio returns and plot the cumulative returns in Panel (a) of Figure 1. The shaded areas are 95% confidence intervals based on Newey-West standard errors with the same number of lags as the event horizon. Consistent with earlier literature, there is positive cross-stock momentum in the short-run, as the long-short portfolio earns a few percentage

of returns one year after portfolio formation. However, the portfolio reverseed subsequently and steadily delivered negative returns in the next fourteen years. Appendix section A.3 shows that our results are robust to alternative ways to combine predictors.

Because firms delist over time, how we treat delistings can matter for long horizon returns. When a firm delists in month t, we assume that it earns the delisting return in that month, and then the remaining value is reinvested into the other stocks starting from month $t+1$. For delisting returns, we use the values reported in CRSP when available. When they are not available, we follow the literature to use -55% for NASDAQ stocks and -30% for the rest (Shumway, 1997; Shumway and Warther, 1999). Appendix A.1 shows that our results are unlikely to be affected by delistings. The fraction of stocks that delist is balanced between the long and short decile portfolios, and our results are robust to alternative delisting treatments (e.g. Hou et al., 2020).

This long-horizon reversal pattern is not specific to the combined predictor, but is true for all nine individual cross-stock momentum predictors. Figure 2 separately plots the cumulative portfolio return computed using the same method for each of the individual predictors. We observe reversal in all cases. While there is variation in the degree of reversals, the point estimate of the cumulative return is negative for all predictors at the fifteen year horizon. That is, by year fifteen after portfolio formation, all cross-stock momentum portfolios have declined more than their original gains.

Is the predictable preversal statistically significant? Table 2 reports the average future returns for long-short cross-stock momentum portfolios. To examine revesals, columns (3) through (5) report 10-, 15-, and 20-year ahead returns after skipping the most recent year. We compute Newey-West standard errors using h-year lags. For all predictors, the point estimate is negative from year h=10, with six out of ten statistically significant at the 5% level. The degree of reversal increases with horizon. By year h=20, all return predictors exhibit statistically significant reversals.



(a) Industry momentum (b) Data-driven (c) BEA customer

(d) BEA supplier (e) Technology link (f) Geographic link

(g) Complicated firms (h) Economic link (i) Analyst coverage

Figure 2. Cross-stock momentum reversals: individual predictors

This figure plots the cumulative 15 year cumulative value-weighted long-short decile returns, where the portfolio as sorted based on nine individual cross-stock momentum predictors. Shaded areas are 95% Newey-West confidence intervals. The predictors are ordered by the time at which they become available.

	Cumulative returns (%)					Standard error (%)				
Horizon:	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	1.16***	3.10***	−8.49***	−6.32***	−10.53***	(0.14)	(0.65)	(2.01)	(1.51)	(1.93)
Industry momentum	0.86***	1.80***	−6.24**	−4.50***	−7.50***	(0.14)	(0.48)	(2.47)	(1.70)	(2.54)
Data-driven	0.89***	1.19**	−0.22	−1.93	−1.23	(0.15)	(0.49)	(3.46)	(1.60)	(3.48)
BEA customer	0.53***	2.75***	−5.87	−4.86**	−7.76**	(0.17)	(0.71)	(4.11)	(2.08)	(3.74)
BEA supplier	0.67***	2.06***	−8.48**	−5.13**	−8.93***	(0.16)	(0.72)	(3.90)	(2.06)	(3.36)
Technology link	0.42**	2.42***	−8.48**	−5.07	−10.31***	(0.19)	(0.78)	(4.04)	(3.40)	(3.58)
Geographic link	0.39***	2.69***	−3.03	−2.44	−5.75**	(0.13)	(0.83)	(2.86)	(2.11)	(2.53)
Economic link	0.53***	1.76***	−3.86	−3.43	−5.69*	(0.16)	(0.66)	(3.75)	(2.66)	(3.42)
Analyst coverage	0.65**	3.42***	−19.76***	−10.34***	−19.74***	(0.29)	(1.17)	(4.24)	(3.41)	(4.92)

Table 2. Returns of cross-stock momentum portfolios.
This table reports post-formation returns of value-weighted long-short decile portfolios sorted on cross-stock momentum predictors. The column names (m, n) refer to cumulative returns from month $t + m$ to $t + n$ where t is the portfolio formation month. The first five columns report cumulative returns in percentage and the last five columns report corresponding Newey-West standard errors. The first row reports results for the combined predictor. The subsequent rows report results for individual predictors ordered by the time at which data for each of them becomes available. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

2.3 Price-level analysis

Notably, in Panel (a) of Figure 1, the degree of eventual return reversal is larger than the initial momentum after portfolio formation. The same is also true for many other individual predictors, as shown in Figure 2. This raises the possibility that the realization cross-stock momentum may represent further exacerbation of *pre-existing* price deviations. That is, the long portfolio of cross-stock momentum is already overpriced relative to the short portfolio upon portfolio formation, and the subsequent momentum returns leads to further deviation from long-run equilibrium. In the language of Van Binsbergen et al. (2023), this means that cross-stock momentum may be a type of "build-up" anomaly.

While cumulative returns of portfolios are informative about deviations in price *levels*, they are not the same, as emphasized by Van Binsbergen et al. (2023) and Cho and Polk (2023). Therefore, in this section, we use the methodology and data from Van Binsbergen et al. (2023) to examine price deviations. They develop a method to measure the degree to which price levels deviate from long-run equilibrium. For the reader's convenience, we briefly describe

their methodology before presenting results.

The price wedge measure. We briefly describe the methodology of Van Binsbergen et al. (2023). For any stock i, conceptually, one can define its present value justified by future payouts:

$$\tilde{P}_{i,t} = E_t \left(\sum_{s=1}^{J} \frac{m_{t+s}}{m_t} \cdot D_{i,t+s} + \frac{m_{t+J}}{m_t} \cdot P_{i,t+J} \right) \tag{2}$$

where $\{D_{i,t+s}\}_s$ represent future dividends, $P_{i,t+J}$ is stock price J periods ahead, and J is a far-enough horizon such that mispricings have mostly dissipated. They use $J = 15$ years in their implementation. $\{m_{t+s}\}$ is a benchmark stochastic discount factor which Van Binsbergen et al. (2023) take to be the CAPM. Then, one can define price wedge as the log deviation of actual price $P_{i,t}$ from the present value-justified price:

$$PW_{i,t} = \log \left(\frac{P_{i,t}}{\tilde{P}_{i,t}} \right) \tag{3}$$

Van Binsbergen et al. (2023) calibrated price wedges using a large number characteristics-sorted portfolios, and then projected the price wedges onto individual stocks. Practically speaking, this means that their price wedge measure will capture the price level deviations associated with the specific set of characteristics they study. We use their stock-level price wedge outputs and refer the reader to their paper for methodological details. We merge our data with theirs which runs from 1964 to 2017.

Price wedge of cross-stock momentum portfolios. To examine whether cross-stock momentum represent a build-up anomaly, we compute the value-weighted price wedge of

long-short NYSE decile portfoilos and plot their evolution in Figure 3.[1] Panel (a) plots the results for the combined cross-stock momentum predictor and the shaded area represents 95% Newey-West confidence intervals. As of the portfolio formation month, the results indicate that the long portfolio is approximately 2% more overvalued relative to the short portfolio, and the difference further exacerbates in the subsequent year as cross-stock momentum return realizes. The price wedge then gradually converge towards zero in the subsequent years.[2]

Panel (b) of Figure 3 plots the same for individual predictors. While there is some disperion, the overall patterns are generally consistent with the idea that cross-stock momentum is a build-up anomaly. In unreported robustness checks, we also find broadly similar results when using the specification in Cho and Polk (2023).[3]

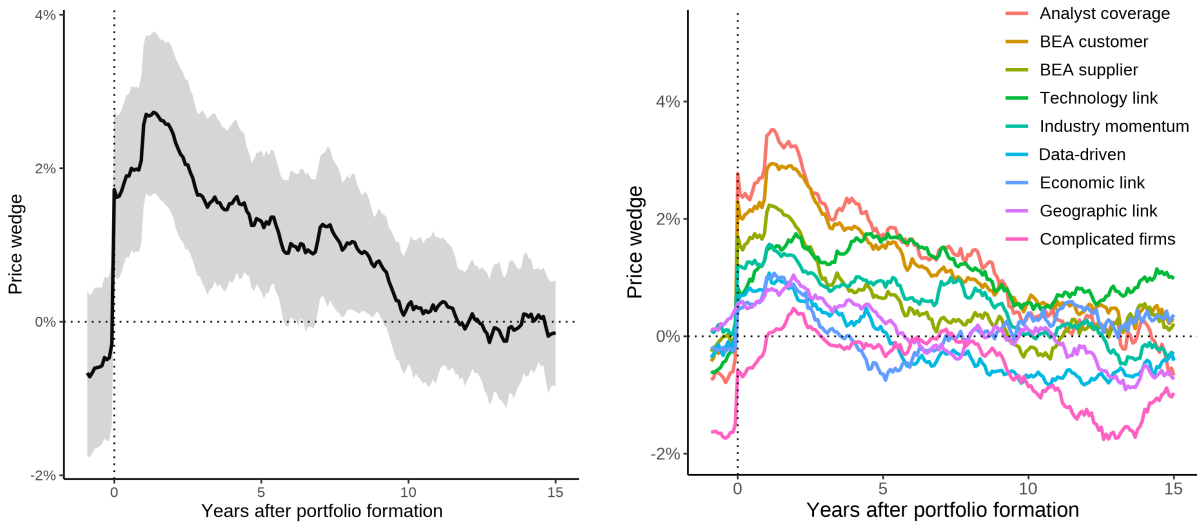
[1]Specifically, we compute:

$$\sum_{i \in S_t^{\text{long}}} w_{i,t} \cdot PW_{i,t+h} - \sum_{i \in S_t^{\text{short}}} w_{i,t} \cdot PW_{i,t+h}$$

where S_t^{long} and S_t^{short} represent the sets of stocks in the long and short decile legs as of sorting month t, $w_{i,t}$ is the market capitalization-based portfolio weight.

[2]While the methodology of Van Binsbergen et al. (2023) only considers the within-15-year return predictability associated with characteristics as part of the price wedge, the finding that price wedge converges towards 0 is not a mechanical result. To see this, suppose there is one characteristic $x_{i,t}$ that predict returns, and its relationship with price wedge is given by $PW_{i,t} = b \cdot x_{i,t}$, where $b > 0$ captures the ability of $x_{i,t}$ to predict returns in the next 15 years. The results in Figure 3 implies that, in the formation month, the long portfolios of cross-stock momentum have higher $x_{i,t}$ than the short portfolio. However, the characteristic differences could have persisted, in which case we would conclude that the price wedge does not converge subsequently.

[3]While using a different methodology, Cho and Polk (2023) also aim to capture the concept of price level deviation using their "adjusted value" measure. We thank the authors for kindly sharing data.



(a) Combined predictor (b) Individual predictors

Figure 3. Price wedge of cross-stock momentum portfolio after formation
We compute the value-weighted Van Binsbergen et al. (2023) price wedge — a measure of price deviation from present value levels — for long-short NYSE decile portfolios sorted on cross-stock momentum predictors. We plot the evolution of price wedge from one year before to 15 years after portfolio formation. Panel (a) examines the combined cross-stock momentum predictor and the shaded areas are 95% Newey-West confidence intervals. Panel (b) examines individual predictors.

3 Dissecting Cross-Stock Momentum

In this section, we examine the component of cross-stock momentum that drives reversal. While cross-stock momentum is often framed in terms of *unidirectional* lead-lag relationships (e.g., stock i leading stock j), some studies suggest that it also contains a common component — where stocks i and j move together, and these shared movements exhibit momentum (e.g. Burt and Hrdlicka, 2021; Yan and Yu, 2023). Building on this literature, we first demonstrate that a significant portion of the long-term returns associated with cross-stock momentum reflects these common movements between peer and focal firms.

This finding provides insight into the origins of reversals, as substantial evidence suggests that common factors exhibit both momentum and long-term reversals, potentially driven by sentiment, capital flows, and other mechanisms (e.g. Lochstoer and Tetlock, 2020; Kelly

et al., 2021; Li, 2022; Ben-David et al., 2024; Wang, 2024). Consistent with this view, we find that the common component largely accounts for reversals. Once this component is removed—isolating purely unidirectional lead-lag effects—reversals disappear entirely, and the remaining component aligns more closely with underreaction: returns materialize within approximately one month and are stronger in stocks with high arbitrage costs. However, this unidirectional component is smaller, explaining only about 40% of cross-stock momentum returns.

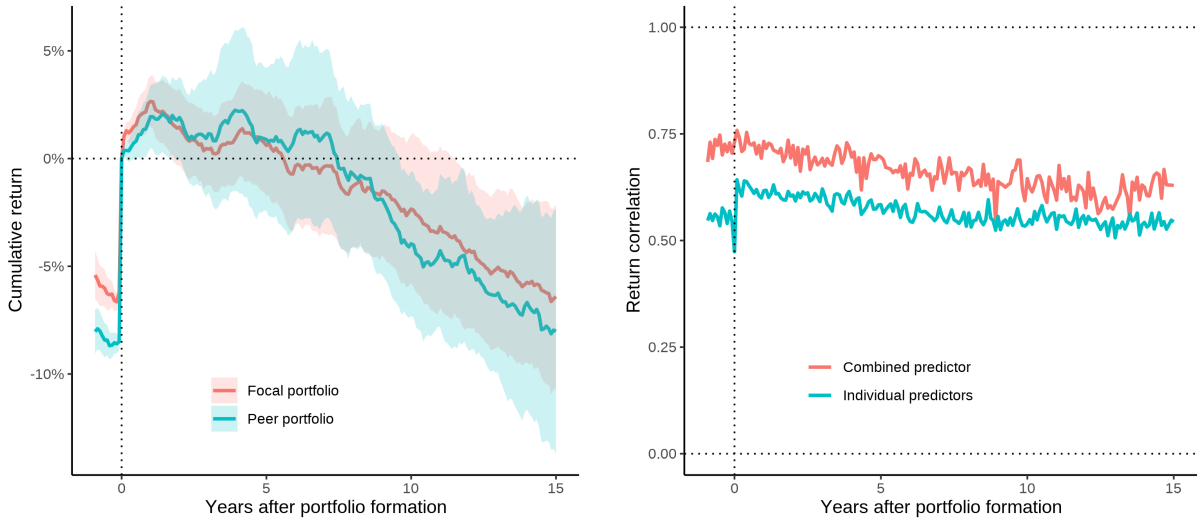
3.1 Common momentum and reversals: preliminary evidence

As discussed earlier, existing literature suggests that cross-stock momentum typically involves unidirectional relationships, with peer stocks leading focal stocks. However, it is also possible that both types of stocks are subject to common shocks that exhibit momentum. For a preliminary examination of this possibility, we start by plotting the cumulative returns of peer portfolios alongside the focal portfolios. Results for the combined predictor is plotted in in Panel (a) of Figure 4.[4] Interestingly, we observe both strong momentum and reversal patterns in the peer portfolios, which is unexpected given that previous studies have primarily focused on unidirectional influences. This new finding is consistent with the idea that results may be driven by common componentss. Appendix A.4 find broadly similar results for all individual predictors.

While Panel (a) plots the *average* return after portfolio formation, Panel (b) of Figure 4 plot the *correlation* of monthly returns between the peer and focal long-short portfolios. The red line plots the correlations for the combined predictor while the blue line plots the average over the individual predictors. The results are consistent with the idea that peer and focal portfolios have significant common components, indicating moderate to strong correlations,

[4]Recall that in cross-stock momentum, each stock i has a peer portfolio of stocks with portfolio weights $\{w_{i,j}\}_{j=1}^{N}$. Then, for a focal portfolio with weights w_i^{focal}, the corresponding peer portfolio has portfolio weights of $\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_i^{\text{focal}} \cdot w_{i,j}}{\sum_i w_i^{\text{focal}}}$ for each stock j.

with values ranging from 0.5 to 0.75.



(a) (b)

Figure 4. Peer versus focal portfolios

We compute value-weighted long-short decile portfolio returns for both focal and peer stocks sorted on cross-stock momentum. Panel (a) plots the cumulative post-formation return for these two portfolios, and the shaded areas are 95% Newey-West confidence intervals. Panel (b) plots the average return correlations between focal and peer portfolios by event period and type of predictor.

3.2 Separating uni-directional lead-lags and common movements

Motivated by this evidence, our objective is to isolate and remove the common return movements from our analysis. To achieve this, we utilize the approach outlined by Yan and Yu (2023), which decomposes cross-stock momentum into "symmetric" and "asymmetric" components. They demonstrate that the 'symmetric' component can be interpreted as common factor momentum, which captures the continuation of returns from factor portfolios.[5] In contrast, the 'asymmetric' component reflects unidirectional lead-lag relationships where stock i leads j but not vice versa.

We briefly describe the methodology and explain how to interpret the two components. Yan and Yu (2023) note that all cross-stock momentum predictors are characterized by

[5]It is worth noting that we use the term "factor" to be synonymous with "portfolios", following the literature on factor momentum. It is a pure statistical description and we take no stance on whether such factors represent economic risks or mispricings.

assumptions on the "prediction matrix," defined as $\Pi = Cov(r_{t+1}, r_t')$, where r_t is an N-vector of stock returns. We consider returns that are demeand by period to focus on cross-sectional relationships. Under this formulation, the predictor for returns r_{t+1} is $s_t = \Pi \cdot r_t$. Under this formulation, different cross-stock momentum predictors can be characterized as using different prediction matrices. Yan and Yu (2023) show that it is instructive to decompose a prediction matrix into symmetric and asymmetric components:

$$\Pi = \underbrace{\left(\frac{\Pi + \Pi'}{2}\right)}_{\equiv \Pi_{\text{sym}}} + \underbrace{\left(\frac{\Pi - \Pi'}{2}\right)}_{\equiv \Pi_{\text{asy}}}. \tag{4}$$

Accordingly, the return predictor can also be split into two components:

$$s_t = \underbrace{\Pi_{\text{sym}} \cdot r_t}_{=s_t^{\text{sym}}} + \underbrace{\Pi_{\text{asy}} \cdot r_t}_{=s_t^{\text{asy}}}$$

The former symmetric component captures momentum in common factor momvements across stocks. To see this, suppose returns have a common factor representation:

$$r_t = B f_t + \epsilon_t$$

where B is an $N \times K$ loading matrix that is unchanged over a short period of time, f_t is the vector of returns of K factors, and ϵ_t is an N vector of return residuals. Further suppose that all lead-lag relationships are captured by autocorrelation in factors:

$$Cov(f_{t+1}, f_t') = \Lambda$$

where Λ is an $K \times K$ diagonal matrix where the diagonal elements capture the autocorrelations of factors. Then, note that the stock-level prediction matrix decomposes into two

parts:[6]

$$\begin{aligned}\Pi &= Cov(r_{t+1}, r_t') \\ &\approx \underbrace{B\Lambda B'}_{\text{factor-based}} + Cov(\epsilon_{t+1}, \epsilon_t')\end{aligned}$$

where the factor-based component is symmetric by construction.

3.3 The common components accounts for the reversal

We first decompose the prediction matrix for each individual cross-stock momentum predictor into two components, as outlined in(4). Next, we compute the symmetric and asymmetric predictors separately, defined as $s_t^{\text{sym}} = \Pi_{\text{sym}} \cdot r_t$ and $s^{\text{asy}} = \Pi_{\text{asy}} \cdot r_t$, respectively. After obtaining these individual predictors, we combine them following the approach described in section 2.1. Specifically, we first convert each individual predictor into unif[-0.5, 0.5] distributions in each cross-section, and then we take an average over the sets of symmetric (asymmetric) predictors to arrive at an aggregate symmetric (asymmetric) predictor. We then conduct the same set of exercises as in section 2 to assess the performance of these aggregated predictors.

Panel (b) of Figure 1 plots the cumulative return to the value-weighted long-short NYSE decile returns to the combined symmetric and asymmetric predictors, separately. As shown in the graph, the reversal occurs exclusively in the symmetric component. Appendix Figure A3 plots the results separately for the first and second halves of the sample and the finding is true for both halves. Appendix Figure A4 find similar patterns in most of the nine individual predictors.

To facilitate a more detailed comparison between the symmetric and asymmetric compo-

[6]The last equality is approximate because we assume the factors and residuals do not cross-predict each other.

nents, we report their average portfolio returns in Table 3. The first immediate observation is that the symmetric component is a more dominant part of cross-stock momentum. In the first three rows which examine the full sample, we see that the total cross-stock momentum effect delivers 1.16% return in the first month, which strengthens into 3.1% by twelve months. The second row shows that the symmetric component accounts for more than half of the expected returns. In contrast, the asymmetric component only delivers 0.37% monthly return, and there is no evidence of further returns beyond one month. While the asymmetric component also generates statistically significant returns at 1-month horizon, the magnitude is smaller, and the return predictability is no longer statistically significant at the one-year horizon. The subsequent rows separately examine subsamples and find similar conclusions.

We also note that long-horizon reversal exclusively happens in the symmetric component. In the full sample, the symmetric component has statistically significant reversal at the future 5-, 10-, and 15-year horizons. In contrast, there is no evidence of reversal in the asymmetric component.

		Cumulative returns (%)					Standard error (%)				
	Horizon:	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Full sample	Total	1.16***	3.10***	−8.49***	−6.32***	−10.53***	(0.14)	(0.65)	(2.01)	(1.51)	(1.93)
	Symmetric	0.68***	2.00***	−6.11**	−4.22**	−7.95***	(0.13)	(0.53)	(2.71)	(1.84)	(2.75)
	Asymemtric	0.37***	0.41	2.49	0.41	1.85	(0.10)	(0.51)	(2.26)	(1.83)	(1.95)
1926-1974	Total	1.24***	2.59***	−6.75***	−5.67***	−8.35***	(0.20)	(0.85)	(2.00)	(1.92)	(1.88)
	Symmetric	0.82***	1.60***	−3.18	−3.83	−4.78*	(0.17)	(0.62)	(2.59)	(2.38)	(2.56)
	Asymemtric	0.38**	0.58	4.07	0.69	3.11	(0.15)	(0.77)	(2.60)	(2.33)	(2.04)
1975-2003	Total	1.08***	3.63***	−10.99***	−7.14***	−13.68***	(0.19)	(0.98)	(3.51)	(2.22)	(2.60)
	Symmetric	0.54***	2.42***	−10.34***	−4.71	−12.51***	(0.19)	(0.86)	(3.90)	(2.96)	(3.84)
	Asymemtric	0.37***	0.24	0.21	0.05	0.05	(0.14)	(0.65)	(2.67)	(3.19)	(2.85)

Table 3. Returns of cross-stock momentum portfolios, with decomposition.

This table reports post-formation returns of value-weighted long-short decile portfolio sorted on the combined cross-stock momentum predictor, decomposed into symmetric and asymmetric components. The column name (m, n) refers to cumulative returns from month $t+m$ to $t+n$ where t is the month of portfolio formation. The first three rows examine the full sample. The next six rows example the first and the second half of the sample. The first five columns report the returns in percent and the five three columns report Newey-West standard errors. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

3.4 The uni-directional residual component

Thus far, the asymmetric component aligns more closely with the standard underreaction theory, which posits that investors take time to adjust their expectations based on new information. This component represents unidirectional lead-lags with no evidence of reversals. In this section, we further document that the asymmetric component is particularly pronounced in stocks with high transaction costs, reinforcing the underreaction theory. In contrast, the symmetric component does not exhibit a stronger presence in illiquid stocks, suggesting a different underlying mechanism.

We proxy the liquidity of stocks using two measures: dollar trading volume and (negative of) bid-ask spread. The former is computed directly from CRSP data. For the latter, we download the bid-ask spread estimated from Corwin and Schultz (2012). To reduce measurement noise, in each month t, we measure liquidity using an exponentially weighted average of the previous twelve monthly values $(t-12, ..., t-1)$ where the exponential weights are determined using forecasting regressions.

To investigate how liquidity affects cross-stock momentum profitability, we divide the sample into three groups based on liquidity measures: those below 20%, those between 20% and 50%, and those above 50%. We use NYSE stocks to create the break points. We then compute the long-short decile value weighted returns for cross-stock momentum within each subsample. The results are reported in Table 4. For both liquidity measures, we find that the asymmetric component exhibits higher return predictability in illiquid stocks, with most differences being statistically significant, indicating a reliable pattern in the data. In contrast, we do not observe similar evidence for the symmetric component, suggesting that its predictability does not vary significantly with liquidity.

	By dollar turnover			By (negative) bid-ask spread		
	Total	Symmetric	Asymmetric	Total	Symmetric	Asymmetric
	(1)	(2)	(3)	(4)	(5)	(6)
Bin 1 (< 20%)	1.29***	0.77***	1.31***	1.72***	0.77***	1.19***
	(0.19)	(0.19)	(0.21)	(0.27)	(0.28)	(0.24)
Bin 2 (20-50%)	1.48***	1.29***	0.75***	1.21***	0.70***	0.56***
	(0.15)	(0.14)	(0.15)	(0.17)	(0.16)	(0.16)
Bin 3 (> 50%)	0.96***	0.62***	0.24**	0.90***	0.55***	0.36***
	(0.15)	(0.13)	(0.12)	(0.13)	(0.12)	(0.11)
Bin 1 - Bin 2	−0.19	−0.52***	0.56***	0.51*	0.06	0.63***
	(0.22)	(0.20)	(0.20)	(0.28)	(0.28)	(0.23)
Bin 2 - Bin 3	0.52***	0.67***	0.51***	0.31**	0.16	0.20
	(0.14)	(0.13)	(0.15)	(0.15)	(0.14)	(0.14)
Bin 1 - Bin 3	0.32	0.16	1.07***	0.82***	0.22	0.83***
	(0.22)	(0.18)	(0.21)	(0.27)	(0.26)	(0.24)

Table 4. Return predictability by liquidity

The table studies the return predictability of the combined cross-stock momentum predictor by liquidity-sorted subsamples. Specifically, we report monthly average returns of long-short decile value-weighted portfolios. The subsamples are stocks in <20%, 20-50%, and >50% NYSE bins, sorted by two liquidity measures: dollar turnover (columns 1 through 3) and the negative of bid-ask spread (columns 4 through 6). Columns (1) and (4) use the total cross-stock momentum predictor. Columns (2) and (5) use the symmetric cross-stock momentum predictor, while columns (3) and (6) use the asymmetric predictor. Standard errors are reported in the parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

4 Alternative methodology to control for common components

To control for common components, in the previous section, we zoom in the asymmetric component of cross-stock momentum. Burt and Hrdlicka (2021) (henceforth BH) proposes a different methodology. They first decompose stock returns into a factor-based component and a residual component:

$$r_{i,t} = a_t + \sum_{k=1}^{K} b_{i,k} \cdot f_{k,t} + r_{i,t}^{\text{resid}} \tag{5}$$

where a_t captures the average return over period t, $\{b_{i,k}\}_{k=1}^{K}$ are factor loadings, and $\{f_{k,t}\}_{k=1}^{K}$

are factor returns. They then only use the return residual $r_{i,t}^{\text{resid}}$ to construct cross-stock momentum predictors for $r_{i,t+1}$.

The BH methodology primarily differs from our approach in that it requires researchers to explicitly specify which factors need to be controlled for in their analysis. In contrast, our method automatically identifies and removes these factor components, streamlining the analysis without requiring prior identification by the researcher. While the BH methodology can achieve similar results, this is contingent upon the researcher accurately identifying all relevant factors, which can be challenging. We provide an analytical demonstration of this distinction in Appendix B.1, illustrating how our method and the BH methodology differ in their handling of factor momentum.

Therefore, propose that, as the set of factors controlled in the BH methodology becomes more comprehensive, the results obtained using this methodology will converge to our findings. Intuitively, when the researcher-specified number of factors K is small, the selected factors may fail to encompass all relevant sources of common momentum, resulting in incomplete control by the BH methodology. However, as the number of factors increases to adequately encompass all relevant common movements, the BH methodology should yield conclusions that align closely with our findings.Section 4.1 empirically illustrates this point by demonstrating how varying the number of controlled factors in the BH methodology affects the results.

4.1 Progressively controlling for more factors

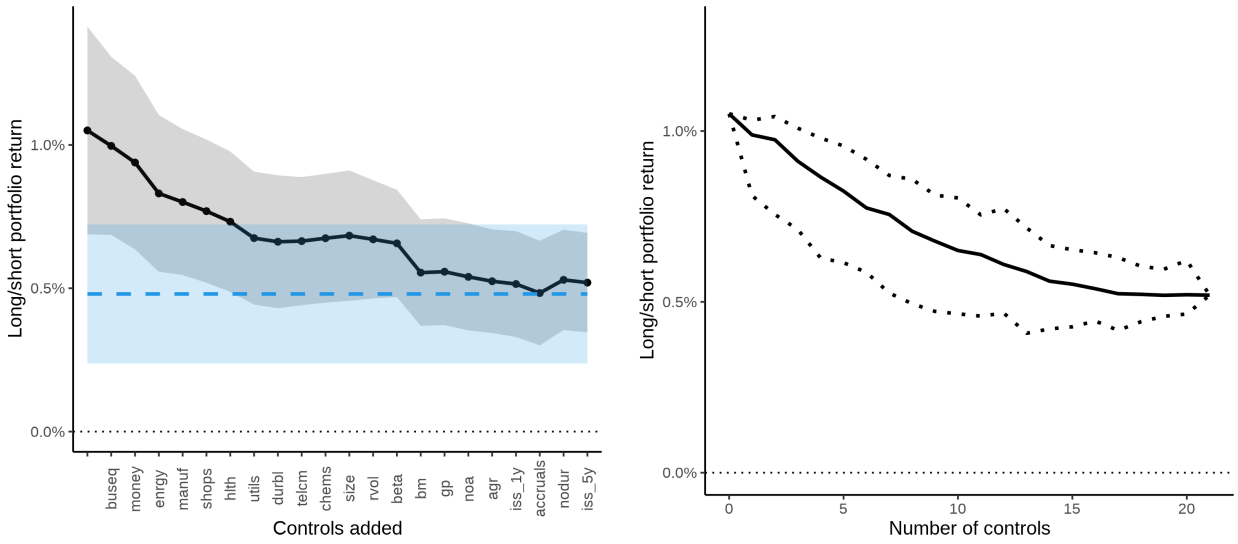
Methodology. IIn alignment with the BH methodology, we control for a set of industry and characteristics-based factors to account for potential influences on cross-stock momentum. To ensure statistical stability, our implementation of the factor model differs slightly from that of BH, while adhering to the methodologies outlined by Fama and French (2020) and common industry practices, such as those used by MSCI Barra. Specifically, we incor-

porate industry dummies and relevant stock characteristics as factor betas in our model, and we infer factor returns through cross-sectional regressions to capture the relationships between these variables and stock performance.

Our implementation starts with industry dummies and a set of commonly used stock characteristics for $\{b_{i,k}\}_{i,k}$ in Equation (5). For the former, we download dummy variables for the Fama-French 12 industry from Professor Ken French's website. For the latter, we download from Chen and Zimmermann (2022) the following characteristics: size, realized volatility, beta, book-to-market, gross profitability, net operating assets, asset growth, 1 year issuance, 5 year issuance, and accruals. Following Kelly et al. (2019), we transform each stock characteristic into uniform distributions over -0.5 to 0.5 by rank in each period. Due to needing characteristics data, we restrict attention to the sample period from 1963.

In the month t, we estimate Equation (5) as a cross-sectional regression. We estimate weighted least squares where the weight of each stock is the square root of its lagged market capitalization, a method that is often used in the industry (e.g. BARRA). We then take the estimated return residuals $r_{i,t}^{\text{resid}}$ to construct cross-stock momentum predictors, and then examine the resulting return predictability on $r_{i,t+1}$.

Results. To assess the impact of additional controls on the combined cross-stock momentum predictor, we progressively add more controls and plot the resulting average long-short portfolio return as depicted by the black line in Panel (a) of Figure 5. The gray areas represent 95% confidence intervals. The plot indicates that, in the absence of controls, the long-short portfolio achieves a monthly return exceeding 1%. As more factors are controlled for, the return declines steadily. Consistent with the previous discussion, as more controls are added, the remaining return predictability converges towards that of the asymmetric component of cross-stock momentum, which is marked by the blue dashed line with 95% confidence intervals in shaded areas. The result is remarkably consistent with the derivations in Appendix B.1 which show that, if sufficiently many factors are being controlled for, the BH



(a) Adding controls

(b) Randomly adding controls

Figure 5. Controlling for factors when constructing cross-stock momentum.

We study the impact of controlling for factor exposures in constructiing cross-stock momentum on its profitability over the sample from 1963. In Panel (a), we progressively control for an expanding set of industry and characteristics-based factors in constructing the cross-stock momentum predictor, and then plot the resulting average monthly return of the long-short NYSE decile portfolio with dark black lines. The shaded gray area represents the 95% confidence interval. The controls added in each step are labeled on the horizontal axis. For comparison purposes, the dashed blue line marks the return of the asymmetric cross-stock momentum portfolio, and the blue shaded area is the 95% confidence interval. In Panel (b), we redo this exercise of iteratively adding controls, but randomize the order in which the controls are added. The solid line plots the median, and the dashed lines plot the 95% confidence interval, of the resulting average portfolio returns.

method should uncover the asymmetric component in the population. In Appendix B.2, we further investigate individual predictors and observe similar conclusions regarding their return predictability in relation to the controls.

In Panel (a) of Figure 5, we first controlled for all Fama-French industries before controlling for stock characteristics. It is worth noting that the former also has substantial explanatory power over returns, which may appear surprising at first glance as industry portfolios are not unconditionally priced. However, they are priced conditionally, and this is why they have explanatory power over cross-stock momentum returns which, as argued earlier, contains

factor/industry momentum components.[7] Ehsani and Linnainmaa (2022b) offer a more in-depth discussion of such time-varying factor controls.

Because industry indicators and stock characteristics are related, the results in Panel (a) should not be interpreted as only the former exhibiting explanatory power. If we reverse the order and control for characteristics first, they also have explanatory power. In constructing factor momentum, Ehsani and Linnainmaa (2022a) note that as long as a sufficiently high number of factors are included, the exact ones used does not make a large difference. Inspired by their finding, we randomize the order in which the controls are added and reestimate the residual long-short portfolio returns. Panel (b) of Figure 5 uses dashed lines to plot the 95% confidence interval over 100 such trials; the solid line is the 50% percentile. The results indicate, indeed, that the result is not sensitive to which exact controls are used.

5 Conclusion

The study of cross-stock momentum has garnered considerable attention in the literature, documenting patterns where the returns of certain stocks predict the returns of related stocks. Understanding these dynamics is crucial for both investors and researchers. We challenge the conventional wisdom that attributes these cross-stock momentum patterns solely to underreaction to cash flow news, suggesting a more complex underlying mechanism. Upon examining longer horizon returns following portfolio formation, we discover that many significant forms of cross-stock momentum exhibit a reversal. Notably, the magnitude of the reversal often exceeds that of the initial momentum, suggesting that cross-stock momentum patterns may reflect prices diverging from, rather than converging towards, long-run equilibrium levels.

To shed light on the reason for such reversals, we note that a significant part of cross-stock

[7] To be concrete, industry portfolios, such as the utilities industry factor, may not have higher expected return than the market portfolio (not unconditionally priced). However, its return may exhibit time-series autocorrelation (is conditionally priced).

momentum does not solely reflect uni-directional lead-lag relationships; instead, it is influenced bycommon factor components (Burt and Hrdlicka, 2021; Yan and Yu, 2023). We decompose cross-stock momentum into two components: a symmetric component that captures common factor momentum and an asymmetric component that reflects unidirectional lead-lag relationships. Our analysis reveals that the symmetric component accounts for a portion of the momentum while fully capturing the observed reversals. In contrast, the asymmetric component, which constitutes approximately one-third of the initial one-month momentum profits, aligns more closely with the underreaction mechanism. This is evidenced by the fact that its profits materialize within approximately one month and are weaker in liquid stocks, suggesting a delayed response to new information. Based on our findings, we recommend that future researchers prioritize the examination of the asymmetric component when investigating underreactions in cross-stock momentum patterns.

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A Additional Empirical Results

A.1 Robustness to alternative delisting treatments

In this section, we provide more details for the delistings for our long-horizon return results in Section 2. Overall, we find that the fraction of delisting to be rather balanced between the long and short deciles, which indicates that differential delisting rates is unlikely to contribute to the long-term reversal pattern we document. Our main results are also robust to alternative delisting treatments. The results are plotted in Figure A1.

Panel (a) plots the cumulative fraction of stocks that survived after portfolio formation. On an equal-weighted basis, around half of stocks survive until after 15 years. On a value-weighted basis, which is more relevant for our analysis which are based on value-weighted portfolios, approximately 71% of stocks survive for 15 years. Panels (b) and (c) further plot survival rates for the long and short deciles separately under value- and equal-weighted bases, respectively, and they show that the survival rates are very similar across these deciles. We also find the survival rates to be similar on deciles 2 to 9 but we do not include them in the graph to avoid overlaying lines.

In Panel (d), we recompute cumulative long-short value-weighted returns in Figure 1 Panel (a) under alternative delisting return treatments. The red line reproduces our baseline result. As discussed in Section 2.2, when CRSP does not have delisting returns, we follow the literature to make assumptions.[8] To examine robustness on our assumptions, the green line plot results if our long-short portfolio rotates out of those stocks one month before delisting so as to not have to rely on assumptions about delisting returns. Finally, the blue line follows the methodology of Hou et al. (2020) where they impute missing delisting returns using those from In Panel (d), we recompute cumulative long-short value-weighted returns in Figure 1 Panel (a) under alternative delisting return treatments. The red line reproduces our baseline result. As discussed in Section 2.2, when CRSP does not have delisting returns, we follow the literature to make assumptions.[9] To examine robustness on our assumptions, the green line plot results if our long-short portfolio rotates out of those stocks one month before delisting so as to not have to rely on assumptions about delisting returns. Finally, the

[8]It is worth noting that this fraction is very small. On a value-weighted basis, only around 0.01% of delisted stocks in our long-short portfolio have missing CRSP delisting returns. This is partially due to us restricting attention to stocks above 20% NYSE market capitalization as microcaps are more likely to have missing delisting returns.

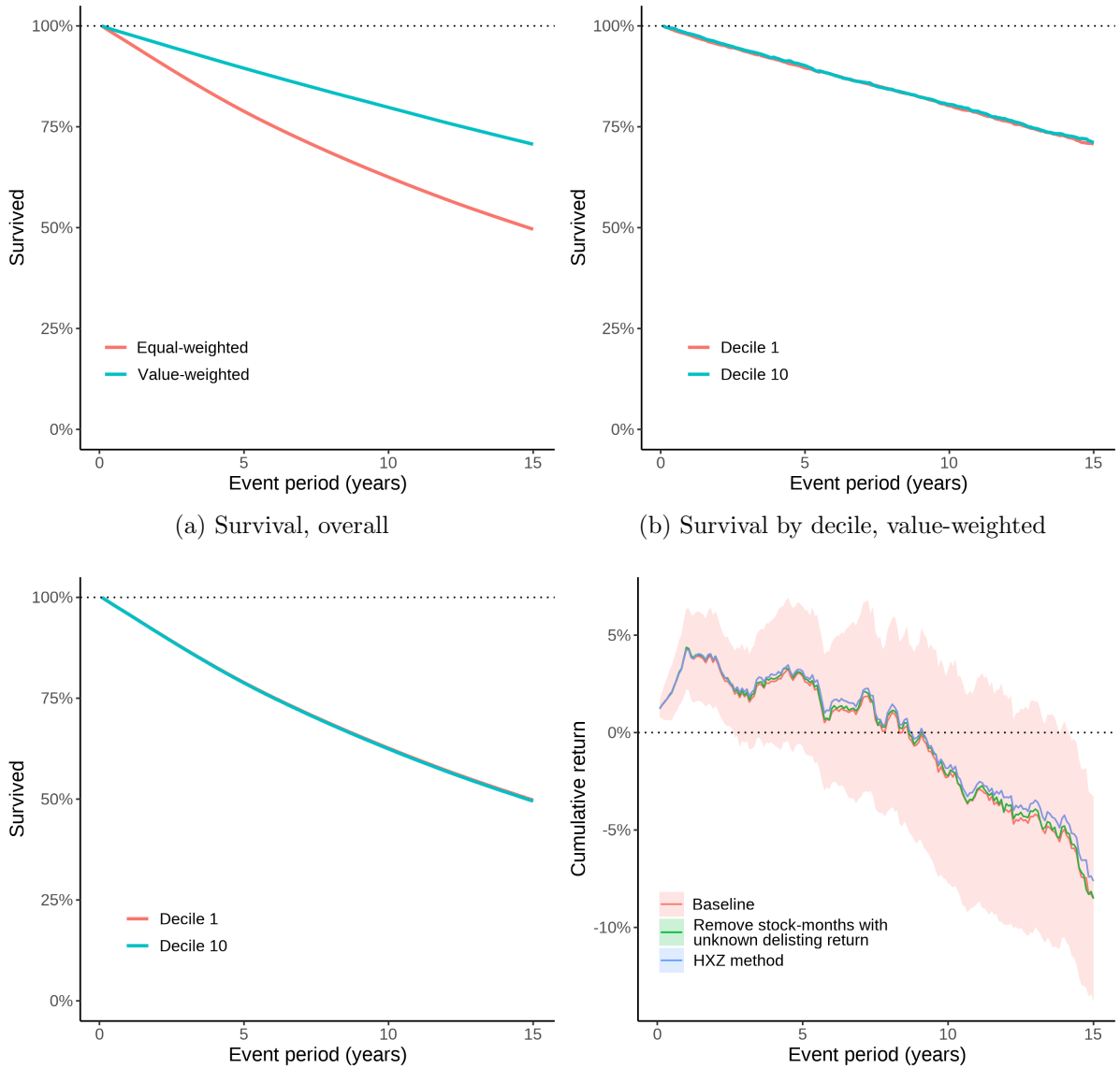
[9]It is worth noting that this fraction is very small. On a value-weighted basis, only around 0.01% of delisted stocks in our long-short portfolio have missing CRSP delisting returns. This is partially due to us restricting attention to stocks above 20% NYSE market capitalization as microcaps are more likely to have missing delisting returns.

blue line follows the methodology of Hou et al. (2020) where they impute missing delisting returns using those from similar stocks in recent periods. All results appear similar under alternative approaches, indicating that our findings are not sensitive to delisting treatment.

A.2 Bootstrapped standard errors

	Cumulative returns (%)					Standard error (%)				
Horizon:	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)	(1,1)	(1,12)	(1,180)	(13,120)	(13,180)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	1.16***	3.10***	−8.49***	−6.32***	−10.53***	(0.15)	(0.63)	(1.52)	(1.38)	(1.43)
Industry momentum	0.86***	1.80***	−6.24***	−4.50***	−7.50***	(0.13)	(0.52)	(1.61)	(1.37)	(1.56)
Data-driven	0.89***	1.19**	−0.22	−1.93	−1.23	(0.17)	(0.53)	(1.80)	(1.37)	(1.82)
BEA customer	0.53***	2.75***	−5.87**	−4.86**	−7.76***	(0.16)	(0.78)	(2.39)	(2.00)	(2.35)
BEA supplier	0.67***	2.06***	−8.48***	−5.13***	−8.93***	(0.19)	(0.62)	(1.96)	(1.60)	(1.99)
Technology link	0.42**	2.42***	−8.48***	−5.07*	−10.31***	(0.18)	(0.81)	(2.60)	(2.63)	(2.56)
Geographic link	0.39***	2.69***	−3.03	−2.44	−5.75***	(0.14)	(0.69)	(2.17)	(1.59)	(2.13)
Complicated firms	0.42***	1.35**	−2.61	−3.12**	−3.88**	(0.15)	(0.52)	(1.91)	(1.58)	(1.79)
Economic link	0.53***	1.76**	−3.86	−3.43**	−5.69**	(0.17)	(0.73)	(2.48)	(1.68)	(2.41)
Analyst coverage	0.65**	3.42**	−19.76***	−10.34***	−19.74***	(0.31)	(1.43)	(3.11)	(2.43)	(2.90)

Table A1. Cross-stock momentum returns with bootstrapped standard errors. This table is the same as Table 2 except that the standard errors are computed using block bootstrap. The block length is determined using the Politis and White (2004) method.



(a) Survival, overall

(b) Survival by decile, value-weighted

(c) Survival by decile, equal-weighted

(d) Cumulative return

Figure A1. Investigating the effect of delisting on main results

This figure examines how stock delisting after portfolio formation affects the main results in Figure 1(a). Panel (a) plots the cumulative fraction of stocks that survive (did not delist) after portfolio formation. Panels (b) and (c) plot the value- and equal-weighted survivoral rates for the long and short decile portfolios, respectively. Panel (d) shows the cumulative long-short portfolio return under alternative delisting return treatments. The red line represents the baseline results under our main specification. The green line omits stock-months with unknown delisting returns, effectively assuming that the strategy rebalances out of those delisting stocks one month before delisting. The blue line follows the delisting treatment in Hou et al. (2020). The shaded areas are 95% confidence intervals for the baseline results.

A.3 Regression-based combination of return predictors

In the main paper, we combine the nine cross-stock momentum predictors by simplying taking stock-level averages, similar to Stambaugh and Yuan (2017). While simple, one may wonder what the results would be if the predictors are combined optimally using a regression framework. In this section, we find that doing so does not materially change the conclusion in the paper.

Regression procedure. To optimally combine all predictors $\{s_{i,t}^l\}_{l=1}^L$ where $L = 9$, we want to weigh them by the coefficients in a panel regression forecasting regression:

$$r_{i,t+1} = \sum_{l=1}^{L} b_l \cdot s_{i,t}^l + \tau_t + \epsilon_{i,t+1} \tag{6}$$

where τ_t are time-fixed effects. Then, we would combine the individual predictors using the estimated coefficients,

$$s_{i,t}^{\text{combined}} = \sum_{l=1}^{L} \hat{b}_l \cdot s_{i,t}. \tag{7}$$

The main implementation difficulty is that the predictors become available at staggered times. To first obtain a full panel of data, we adopt the procedure in Berk and Van Binsbergen (2015) to recursively impute the missing predictors using others. Specifically, we start with the predictor that came the latest: analyst coverage which became available in 1983. We use the joint data after 1983 to estimate a regression of the analyst coverage predictor onto the other ones, and then use this relationship to imput values over 1978 to 1982. We then repeat the same procedure for the economic link predictor which becomes available in 1978, and so on. Thus, we iteratively impute all predictors using this recursive procedure.

We then estimate the panel regression (6), and the result is reported in column (1) of Table A2. The results indicate that all predictors have marginal explanatory power for future returns. With the exception of the BEA supplier predictor, each coefficient is statistically significant at the 1% level. Columns (2) through (10) report univariate regressions and confirm that they all have significant explanatory power over future returns. We then use the point estimates in column (1) to construct the combined return predictor, as in equation (7).

	Dependent variable: $r_{i,t+1}$ (in %)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
indu	0.824***	1.329***								
	(0.10)	(0.15)								
crossmom	0.520***		0.764***							
	(0.10)		(0.11)							
beacustomer	0.418***			1.313***						
	(0.13)			(0.20)						
beasupplier	0.208				1.118***					
	(0.17)				(0.22)					
tec	0.526***					1.342***				
	(0.20)					(0.28)				
geo	0.348***						0.335***			
	(0.09)						(0.09)			
pseudo	0.593***							0.578***		
	(0.12)							(0.12)		
econ	0.503***								0.877***	
	(0.11)								(0.13)	
analyst	1.338***									2.004***
	(0.33)									(0.38)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341	3,479,341
Within R^2	0.11%	0.05%	0.00%	0.04%	0.03%	0.01%	0.00%	0.01%	0.01%	0.06%

Table A2. Combining predictors using regression

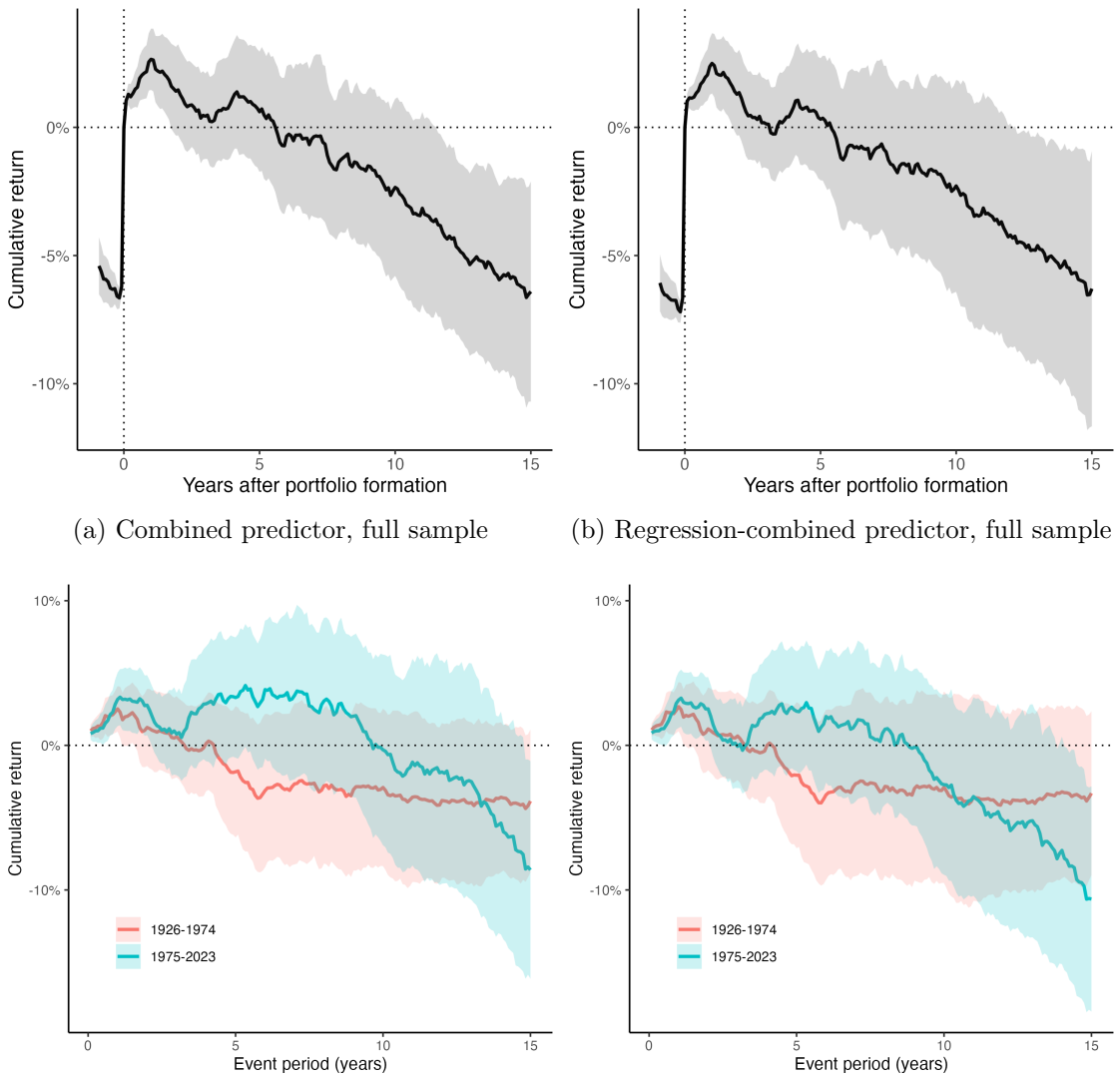
We estimate panel regressions of monthly stock returns on cross-stock momentum predictors, which have been transformed to uniform [-0.5, 0.5] distributions by rank in each cross-section. Column (1) includes all predictors, while the other columns examine one predictor at a time. All regressions control for time fixed effect and cluster standard errors by time and stock. The predictors that are only available for a subset of data are imputed via linear projections on the others, as described in Appendix A.3. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Results. The regression-combined predictor is not too different from our simple average-based combined predictor. The average cross-sectional rank correlation between the two is 0.94, which indicates that they would assign similar stocks to long and short portfolios.

To verify that they yield highly similar results, we compare long-horizon returns based on the two combined predictors side-by-side in Figure A2. Panel (a) reproduces Panel (a) of Figure 1, which shows that the long-short portfolio formed using the average-combined predictor reverts. Panel (b) plots the results based on the regression-combined predictor, with very little difference. Panels (c) and (d) separately examine the first and second halves of the sample, and also find little difference between the two methods of combining predictors.

A.4 Evidence of common momentum and reversals

Figure A6 plots the post-formation cumulative return of peer and focal portfolios for individual predictors.



(a) Combined predictor, full sample

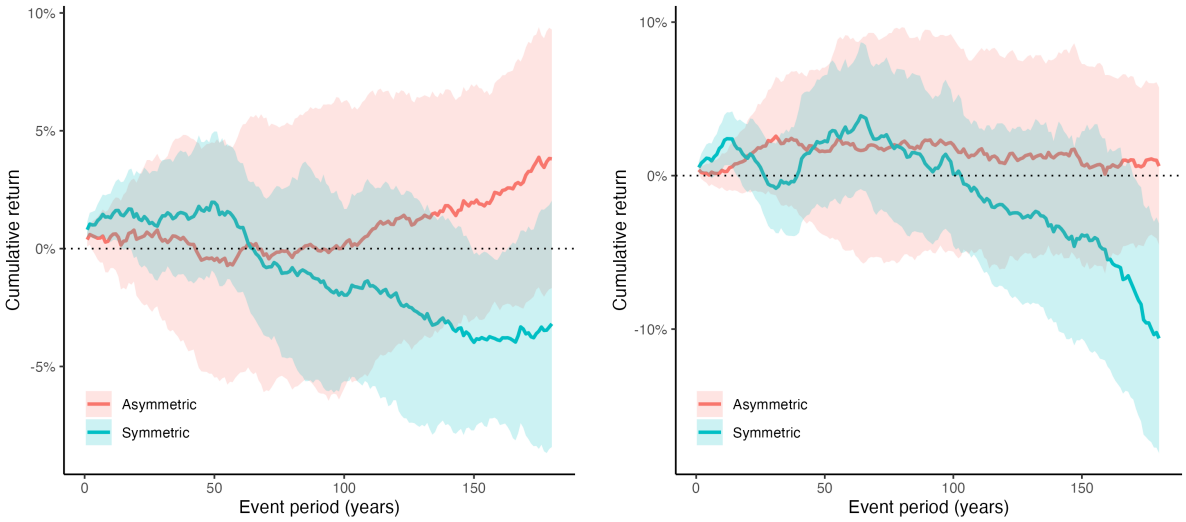
(b) Regression-combined predictor, full sample

(c) Combined predictor, sub sample

(d) Regression-combined predictor, sub sample

Figure A2. Cross-stock momentum reversals: robustness

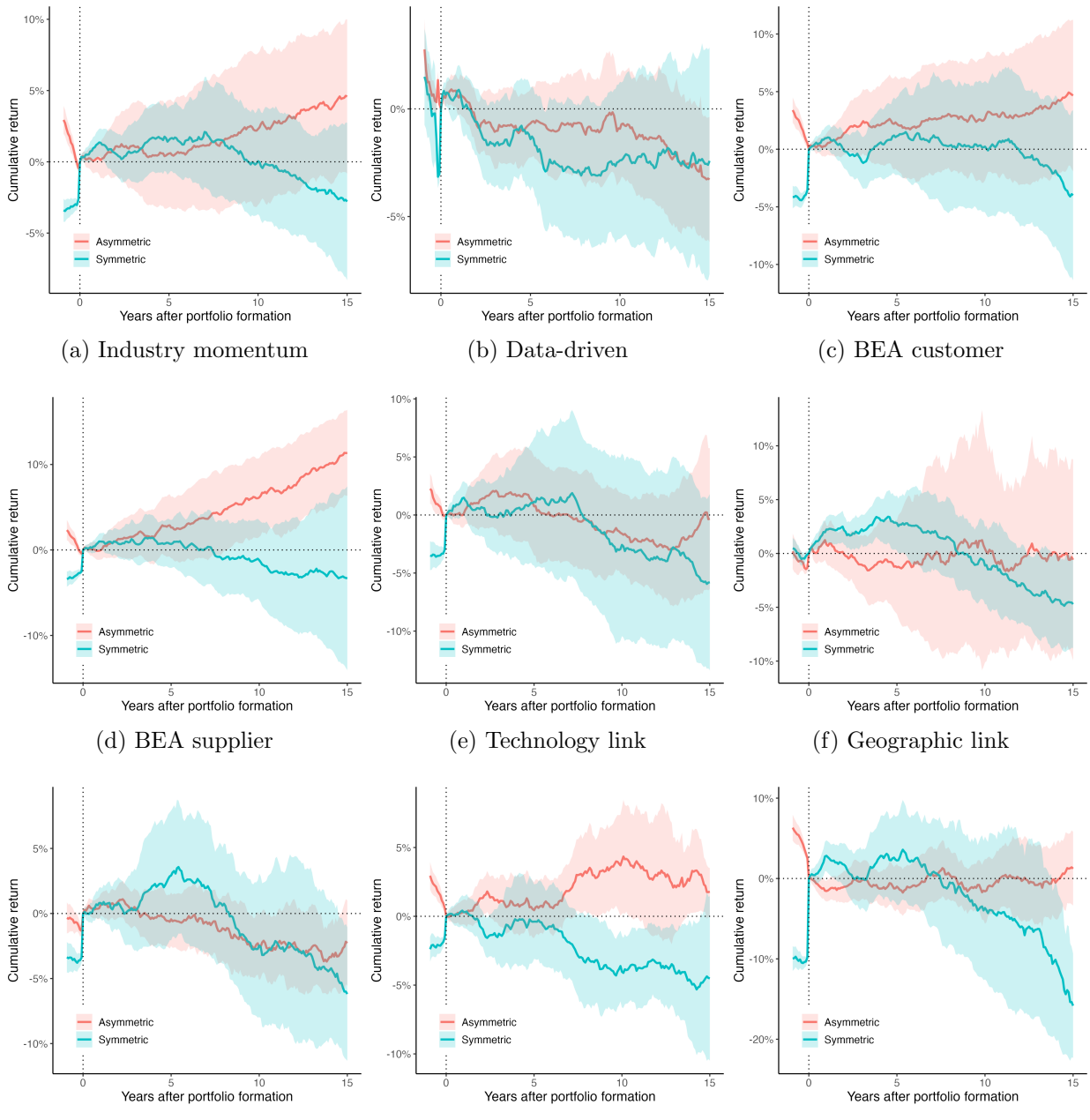
Panel (a) reproduces Panel (a) of Figure 1. Panel (b) conducts the same analysis using an alternative, regression-based approach to combine predictors. Panels (c) and (d) reconduct the same analysis using subsamples.



(a) 1926 - 1974

(b) 1975 - 2023

Figure A3. Returns of symmetric/asymmetric predictors: sub-samples. This figure plots the cumulative return of the value-weighted long-short NYSE decile portfolios formed using the symmetric and asymmetric components of the combined predictor. Panels (a) and (b) plot the first and second halves of the sample, respectively. Shaded areas are 95% Newey-West confidence intervals.



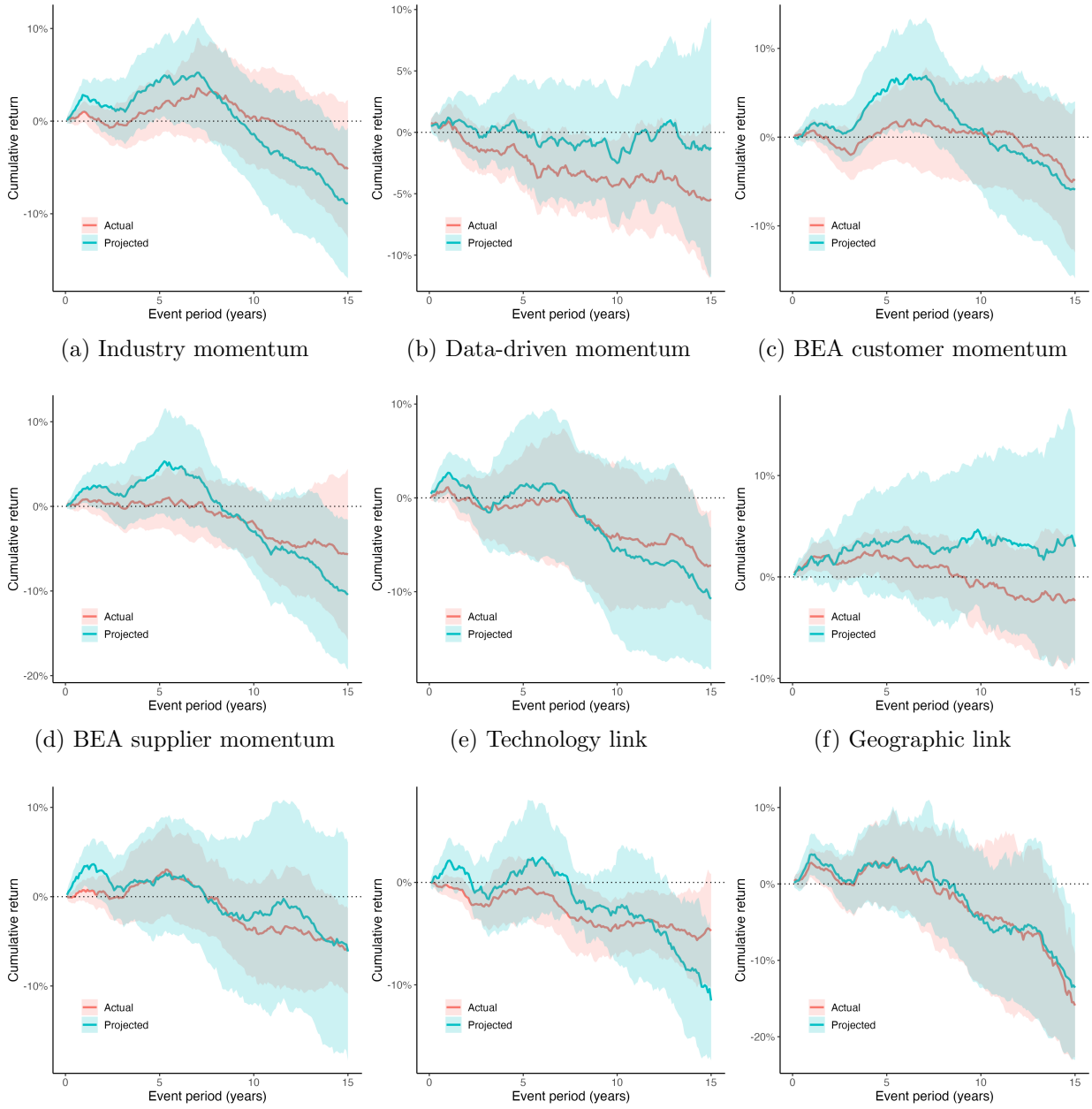
(a) Industry momentum (b) Data-driven (c) BEA customer

(d) BEA supplier (e) Technology link (f) Geographic link

(g) Complicated firms (h) Economic link (i) Analyst coverage

Figure A4. Cross-stock momentum decomposed: individual predictors

This figure plots the cumulative 15-year return to value-weighted long-short decile returns based on nine individual cross-stock momentum predictors, decomposed into the symmetric and asymmetric components. Shaded areas are 95% confidence intervals. The predictors are ordered by the time at which they become available.



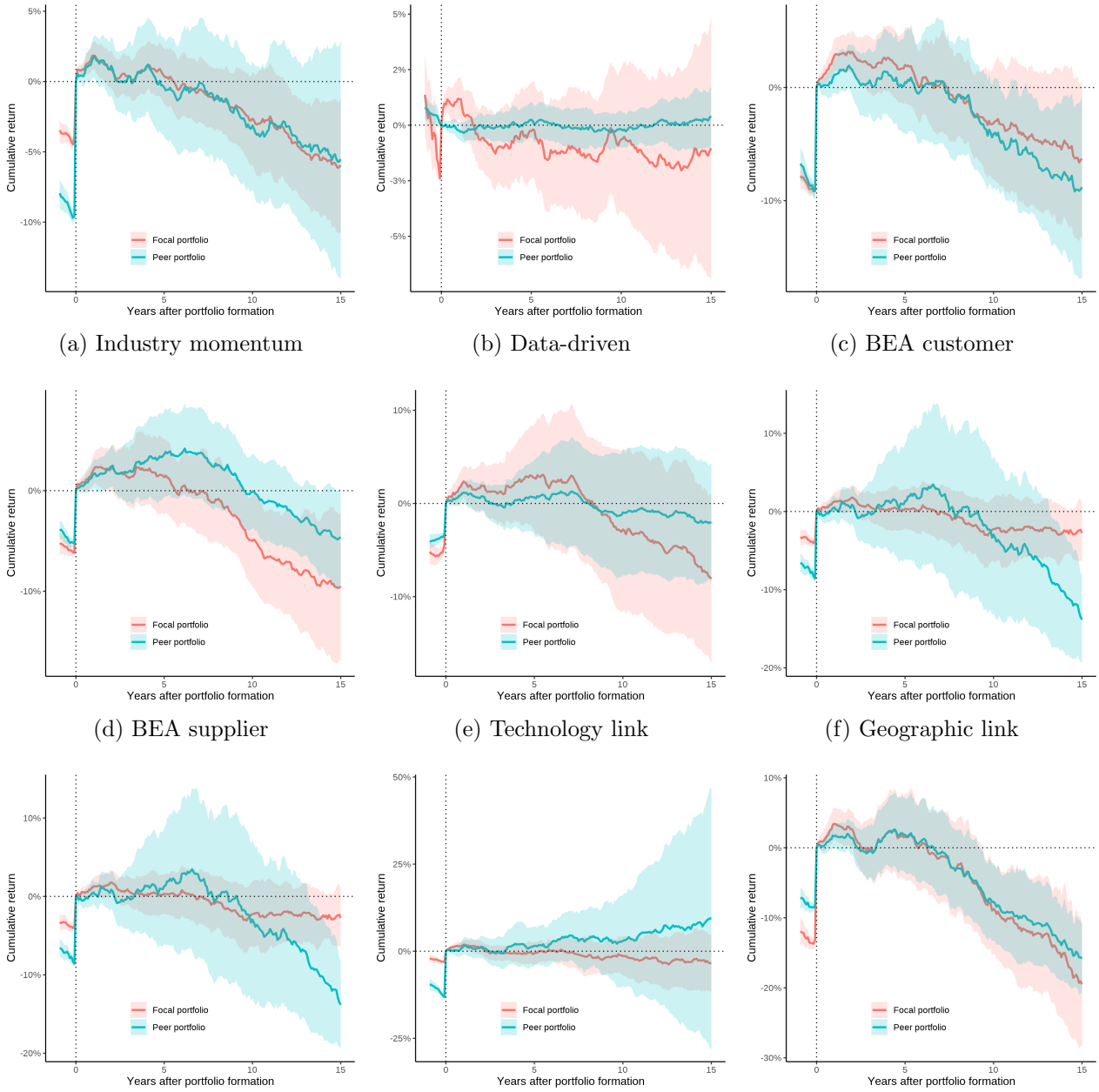
(a) Industry momentum (b) Data-driven momentum (c) BEA customer momentum

(d) BEA supplier momentum (e) Technology link (f) Geographic link

(g) Complicated firms (h) Economic link (i) Analyst coverage

Figure A5. Projection of symmetric cross-stock momentum onto characteristics: individual predictors

This figure plots the cumulative 15-year return to value-weighted long-short decile returns based on the symmetric parts of nine individual cross-stock momentum predictors. The red lines plot the actual predictors and blue lines plot results after projecting the predictors onto commonly-used stock characteristics. Shaded areas are 95% Newey-West confidence intervals. The predictors are ordered by the time at which they become available.



(a) Industry momentum (b) Data-driven (c) BEA customer

(d) BEA supplier (e) Technology link (f) Geographic link

(g) Complicated firms (h) Economic link (i) Analyst coverage

Figure A6. Peer vs focal portfolios: by predictor

This Figure is the same as Panel (a) of Figure 4 but for each individual predictor.

B Alternative Ways to Control Common Components

B.1 Using residual returns to construct predictors

In this section, we analytically compare the methodology of Burt and Hrdlicka (2021) to ours in controlling for factor exposures in cross-stock momentum. The following derivation ignores estimation uncertainty and assumes that the factor loadings and returns can be precisely known.

Data generating process. Let r_t be an N-vector of stock returns after subtracting the market (to focus on cross-sectional variation). Suppose it can be decomposed into a factor and an idiosyncratic component:

$$r_t = B \cdot f_t + \epsilon_t$$

where B is an $N \times K$ matrix of loadings that is constant over a short period of time, f_t is a K-vector of factor returns, and $\epsilon_t \sim N(\alpha_{t-1}, \Sigma_\epsilon)$ are idiosyncratic residuals (so $Var(\epsilon_t)$ is a diagonal matrix). Further hypothesize that the factors exhibit factor momentum, so the matrix

$$Cov(f_{t+1}, f_t') = \Pi_f$$

has positive diagonal elements.

The relationship between two methodologies.

- **Yan and Yu (2023) methodology**. In the notation of Section 3.2, the prediction matrix which captures all lead-lag relationships, is

$$\begin{aligned}\Pi &\equiv Cov(r_{t+1}, r_t') \\ &= Cov(Bf_{t+1} + \epsilon_{t+1}, f_t'B' + \epsilon_t') \\ &\approx B \underbrace{Cov(f_{t+1}, f_t')}_{\equiv \Pi_f} B' + \underbrace{Cov(\epsilon_{t+1}, \epsilon_t')}_{\equiv \Pi_\epsilon}\end{aligned}$$

  where we have assumed that the lead-lag covariance between factor and idiosyncratic components, $Cov(\epsilon_{t+1}, f_t')$ and $Cov(f_{t+1}, \epsilon_t')$, are small. The symmetric-asymmetic de-

composition method in this paper would separate:

$$\begin{aligned}\Pi &= \frac{\Pi + \Pi'}{2} + \frac{\Pi - \Pi'}{2} \\ &= \underbrace{B\Pi_f B' + \frac{\Pi_\epsilon + \Pi'_\epsilon}{2}}_{=\Pi_{\text{sym}}} + \underbrace{\frac{\Pi_\epsilon - \Pi'_\epsilon}{2}}_{=\Pi_{\text{asy}}}.\end{aligned}$$

Therefore, by removing the symmetric component, the Yan and Yu (2023) methodology automatically removes all factor momentum, as well as residual momentum as captured by $\frac{\Pi_\epsilon + \Pi'_\epsilon}{2}$.

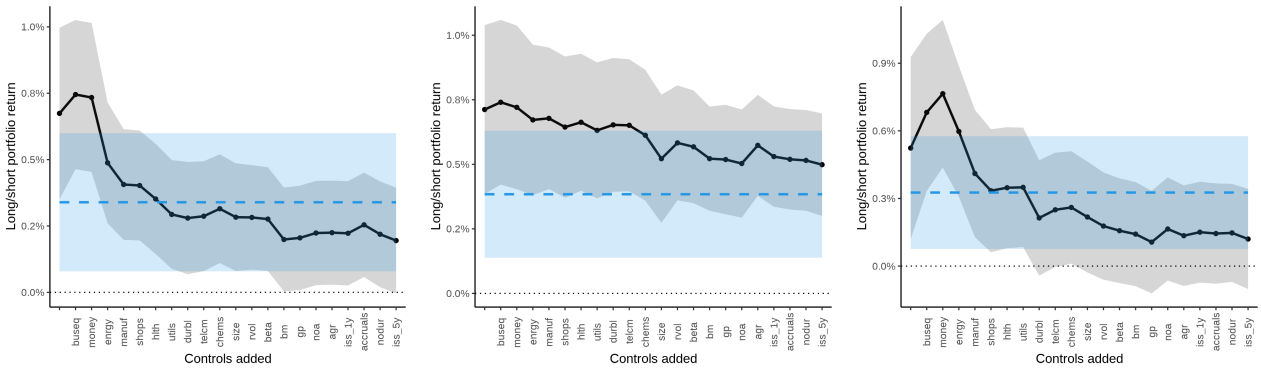
- **Burt and Hrdlicka (2021) methodology**. If all factors are controlled for, the resulting lead-lag relationships that remains is:

$$Cov(r_{t+1}, \epsilon'_t) \approx Cov(\epsilon_{t+1}, \epsilon'_t)$$

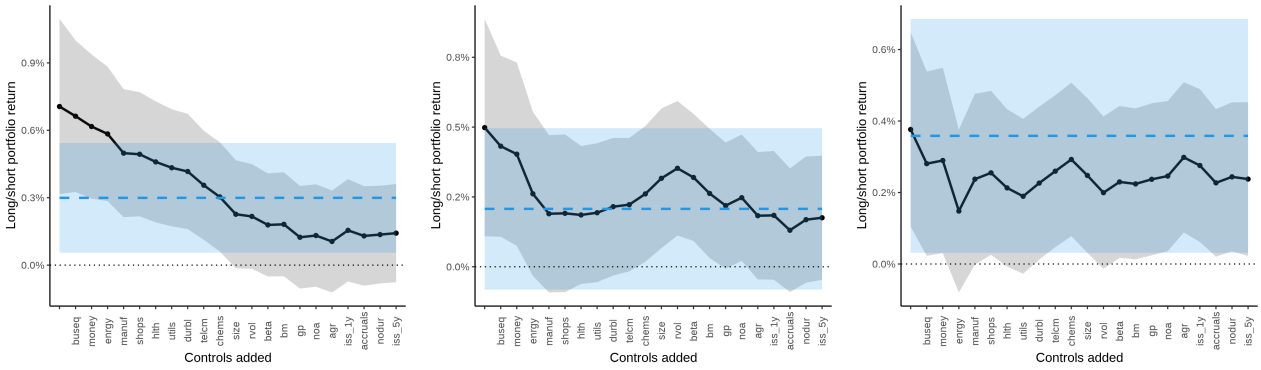
Therefore, this methodology also removes the factor-based component.

B.2 Results by predictor

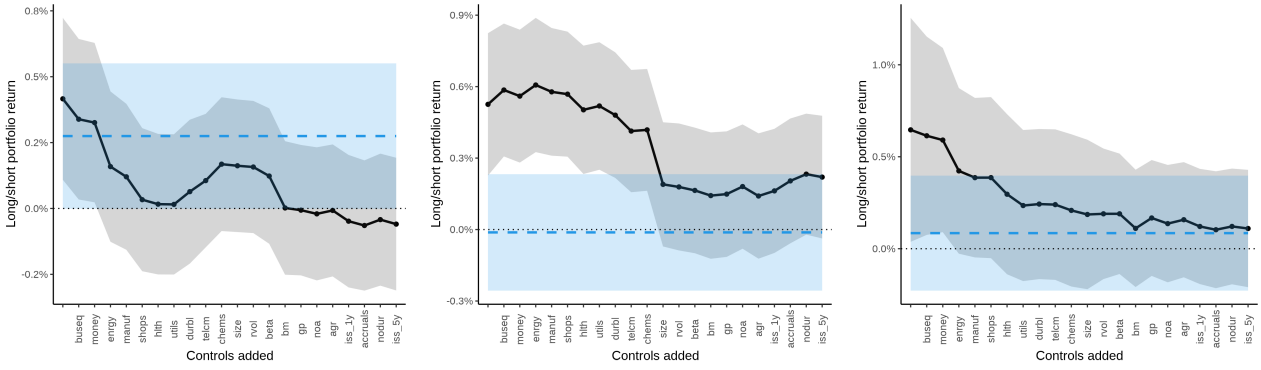
Figure B7 is similar to Panel (a) of Figure 5 but plotted for individual cross-stock momentum predictors. The graphs appear in the order in which each predictor becomes available.



(a) Industry momentum (b) Data-driven (c) BEA customer



(d) BEA supplier (e) Technology link (f) Geographic link



(g) IComplicated firms (h) Economic link (i) Analyst coverage

Figure B7. Progressively controlling for factors: by predictor

This Figure follows Panel (a) of Figure 5, and plot separately for individual cross-stock momentum predictors. The predictors are ordered by the time at which they become available.