How Much of Cross-Stock Momentum Reflects Underreaction? *

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Jiacui Li and Jingda Yan

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ABSTRACT

Numerous studies document cross-stock momentum (CSM) effects — situations where returns of related stocks cross-predict each other — and interpret these patterns as underreaction to cash flows. However, we find that these returns revert over the long run, which suggests that additional mechanisms are at play. Further examination reveals that existing CSM findings are not limited to unidirectional lead-lag relationships from the peer firms to focal firms. Instead, they incorporate common movements among these stocks, and those common components exhibit short-run momentum followed by long-run reversals. After removing these common components, the residual CSM aligns more closely with the underreaction hypothesis: returns do not revert and are stronger in stocks with higher trading costs. We propose a method to systematically remove common components from CSM, and we find that close to half of the previously documented CSM effects remain.

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 Usman Ali, Aaron Burt, Aditya Chaudhry, Sina Ehsani, David Hirshleifer, Christopher Hrdlicka, Allen Hu, Charles Lee, Ali Sharifkhani, Yang Song, Stephen Teng Sun, Jialin Yu, and presentation participants at Fudan School of Management, Monash Business School, NJIT, NYU Shanghai, Purdue, University of Queensland, and Utah. We thank Andrea Tamoni for sharing data. The authors have no conflicts of interest to report.

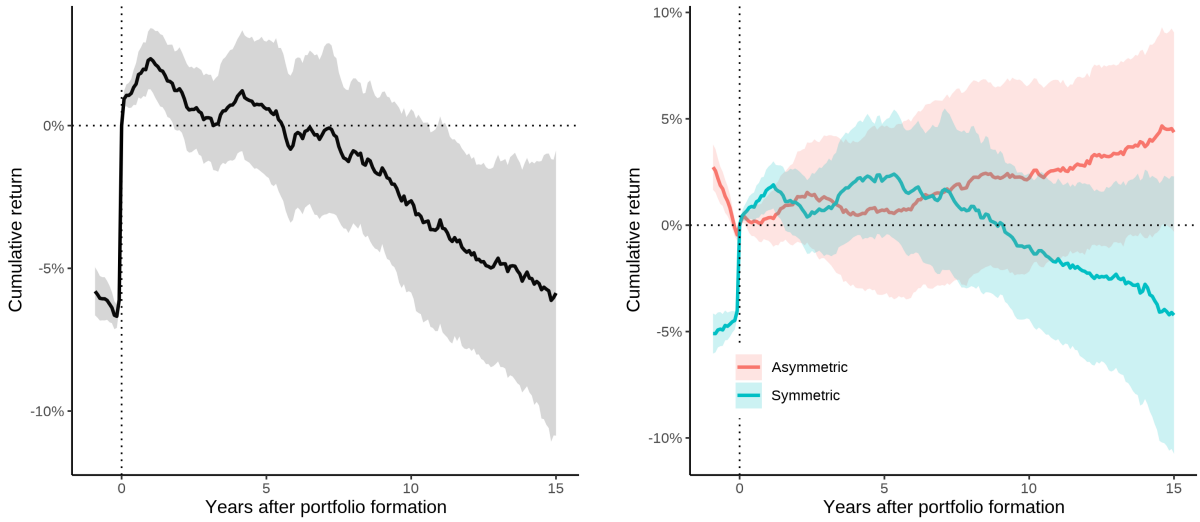
1 Introduction

A substantial body of literature documents cross-stock momentum (CSM) patterns, where the returns of related "peer" stocks predict the returns of "focal" stocks. For example, Cohen and Frazzini (2008) find that the returns of customer firms predict those of suppliers. Similar patterns are observed among stocks in the same industry (Moskowitz and Grinblatt, 1999), geographic region (Parsons et al., 2020), with similar technological profiles (Lee et al., 2019), or overlapping analyst coverage (Ali and Hirshleifer, 2020). These findings are typically interpreted as underreaction to cash flow information, possibly due to investor inattention or segmentation (e.g. Menzly and Ozbas, 2010).

If underreaction to cash flow information were the sole mechanism underlying CSM, the returns would not revert (Samuelson, 1965). However, we document that CSM returns do revert in the long run, suggesting the presence of alternative mechanisms. To explore the source of these reversals, we show that a significant component of CSM reflects common movements between peer and focal stocks, explaining more than half of the initial momentum and all of the reversals. After removing this common component, the remaining CSM returns — just under half of the total — are driven by unidirectional lead-lag relationships, which aligns more closely with the traditional underreaction explanation. Based on these findings, we suggest that future studies of CSM patterns conduct similar decompositions and exercise caution in interpreting the common components as reflecting underreaction.

We begin by documenting long-run return reversals. Replicating eight prominent CSM predictors, we find that their initial returns consistently reverse in the years following portfolio formation, similar to the reversal patterns observed in stock momentum (Lee and Swaminathan, 2000; Jegadeesh and Titman, 2001). For ease of exposition, we focus on a combined predictor that averages across all individual CSM predictors. In Panel (a) of Figure 1, we plot the cumulative returns of value-weighted, long-short NYSE decile portfolios sorted by this combined CSM predictor. Consistent with the literature, the portfolio shows high returns

within twelve months of formation. However, the returns reverse subsequently. The point estimate in forecasting regressions suggests a full reversal after approximately five years, and the reversal is statistically significant. While we present most of our findings using this combined predictor, the results are robust across all individual CSM predictors. These findings indicate that CSM returns cannot be solely attributed to underreaction to cash flow news.



(a) Cross-stock momentum

(b) Decomposed cross-stock momentum

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

We analyze the cumulative returns of long-short, value-weighted NYSE decile portfolios sorted by cross-stock momentum (CSM). The sorting variable, detailed in Section 2.1, is the average of eight individual CSM predictors from the existing literature. Panel (a) shows cumulative returns from one year before to fifteen years after portfolio formation. Panel (b) further decomposes the predictor into symmetric and asymmetric components — reflecting common momentum and unidirectional lead-lag relationships, respectively — and examines long-short portfolios formed using each. The decomposition is explained in Section 3. In both panels, shaded areas represent 95% Newey-West confidence intervals.

Over a ten- to fifteen-year horizon, the eventual reversal surpasses the original CSM returns in magnitude, and the difference is statistically significant. To the extent that prices converge to equilibrium levels in the long run, this suggests that CSM is a "build-up" anomaly, where prices initially move further away from equilibrium before correcting (Van Binsbergen et al., 2023). This contrasts with earlier literature, which conceptualizes CSM as a "resolution" anomaly, where returns represent convergence toward long-run equilibrium. To corroborate our return-based findings, we also examine the mispricing *level* measure developed by

Van Binsbergen et al. (2023) and find qualitatively consistent results.[1]

To better understand the source of the reversal, we observe that, contrary to common intuition, CSM predictors do not solely reflect unidirectional lead-lags from peer stock A to focal stock B. Existing studies also show that returns of B can predict those of A. In other words, there are common components shared by A and B (e.g. Burt and Hrdlicka, 2021). We hypothesize that these common components account for the long-run reversals. To test this hypothesis, we examine return predictability not only in focal firms, as in previous studies, but also in peer firms. After portfolio formation, the peer firm portfolios exhibit similar momentum and reversal patterns that are highly similar to the focal firms, which is consistent with our hypothesis.

Building on the observation above, we formally filter out the common component to isolate the part of CSM more likely driven by underreaction. Following Yan and Yu (2023), we decompose CSM into a symmetric and an asymmetric component. This decomposition relies on the fact that all existing CSM predictors can be represented by an $N \times N$ prediction matrix Π, where the predictor vector for r_{t+1} — the vector of next-period stock returns — is simply $s_t = \Pi \cdot r_t$. We then split s_t into two additive parts:

$$\Pi \cdot r_t = \underbrace{\left(\frac{\Pi + \Pi'}{2}\right) \cdot r_t}_{\equiv \Pi_{\text{sym}} \cdot r_t = s_t^{\text{sym}}} + \underbrace{\left(\frac{\Pi - \Pi'}{2}\right) \cdot r_t}_{\equiv \Pi_{\text{asy}} \cdot r_t = s_t^{\text{asy}}}. \tag{1}$$

We show that the symmetric component captures momentum in common factors, while the asymmetric component reflects unidirectional lead-lags between stocks. Consistent with this interpretation, the symmetric component explains nearly all of the correlation between peer and focal portfolios.

[1] Of course, this interpretation applies only if CSM is considered an anomaly. If CSM patterns reflect discount rate movements, our findings imply that the direction of these movements changes after portfolio formation.

We argue that the residual asymmetric component aligns more closely with the underreaction explanation. It captures unidirectional lead-lags between stocks, does not revert, and exhibits stronger return predictability in stocks that are harder to arbitrage. Quantitatively, the asymmetric component accounts for approximately one-third to half of the initial one-month CSM returns and about one-fifth of the returns within the first twelve months after portfolio formation. These findings suggest that while CSM does reflect some underreaction effects, their magnitude is smaller than previously believed.

What about the symmetric component? It is correlated with the peer portfolios and accounts for all of the reversals. These findings make it challenging to interpret the whole symmetric component as reflecting underreaction. We further show that this component is related to the factor-momentum of Arnott et al. (2023), which we show to also exhibit long-run revresals. 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 findings are robust to alternative methods for controlling common factor components. Burt and Hrdlicka (2021) propose an approach that first obtains return residuals by controlling for known factor exposures (e.g., size) and then constructs CSM predictors using these residuals ($s_t^{\text{resid}} = \Pi \cdot r_t^{\text{resid}}$). Intuitively, if factor loadings could be estimated without uncertainty, their approach would converge to ours as the number of controlled factors grows large enough to span the entire common component. Consistent with this intuition, as we progressively control for industry and commonly used characteristics-based factors, estimates from this regression-based method increasingly align with ours across most dimensions.

The main contribution of this paper is a nuanced interpretation of CSM. We show that existing CSM findings inadvertently include a sizeable common component that reverts over the

long run, indicating that not all CSM patterns stem from underreaction to cash flows. Based on our findings, we recommend that future research control for this common component to better isolate unidirectional lead-lag effects, which are more likely to reflect underreaction. As a byproduct, we also document that factor momentum reverses over time, a phenomenon not previously highlighted in the literature (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023).

This paper is related to Burt and Hrdlicka (2021) who are the first to argue that CSM incorporates common momentum. Our symmetric-asymmetric decomposition is inspired by Yan and Yu (2023), who base their analytical framework on the analysis of Kelly et al. (2023). Our analysis of long-run return patterns in CSM parallels findings in the stock momentum literature, where Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) document return reversals, supporting the "continued overreaction" view of momentum (e.g. Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999) rather than solely underreaction. Additionally, our work contributes to the factor momentum literature (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023) by demonstrating that factor momentum also exhibits long-term reversals.

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 mitigate the influence of small or illiquid stocks, we exclude those with prices below $5 per share and those with lagged market capitalization below the 20th percentile of NYSE stocks. Our sample spans from 1926 to 2023. When no additional variables are required, it includes a total of 1,682,616 stock-month observations, with an average of 1,416 stocks per month. We obtain stock characteristics data from Chen and

Zimmermann (2022).

Cross-stock momentum (CSM) predictors. We replicate eight prominent CSM predictors studied in the prior literature. To mitigate concerns of cherry-picking, we pick the same list of predictors as those studied in Yan and Yu (2023). Table 1 summarizes these predictors by the order in which data becomes available. The one-month industry momentum predictor of Moskowitz and Grinblatt (1999) is available from the start of the sample. The BEA customer- and supplier-based predictors from Menzly and Ozbas (2010) become available in 1952, followed by the technology link-based predictor of Lee et al. (2019) in 1963, 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 1978, and the analyst co-coverage-based predictor of Ali and Hirshleifer (2020) in 1983. Columns (4) and (5) of the table report the equal- and value-weighted fraction of stocks with available predictor values. On a value-weighted basis, the industry and analyst coverage predictors encompass most stocks, while the others vary in coverage. The geographic link predictor has the lowest coverage, capturing slightly less than half of the stock universe. To ensure comparability across predictors, we follow the return predictability literature (e.g., Kelly et al., 2019) and transform them into uniform distributions ranging from -0.5 to 0.5 using cross-sectional ranks.

As discussed in the introduction, most of these CSM effects have been interpreted as evidence of underreaction to cash flow information. In unreported tests, we verify that we can closely replicate the main findings of these papers.

A combined CSM predictor. To simplify exposition, much of our empirical analysis uses a combined predictor that aggregates the eight individual CSM predictors. Following Stambaugh and Yuan (2017), we compute this combined predictor as the average of all available predictor values. For example, between 1953 and 1962, it is derived from the three

Predictor	Paper	Start	Firms	Coverage	
				EW	VW
	(1)	(2)	(3)	(4)	(5)
Industry momentum	Moskowitz and Grinblatt (1999)	1926	1,325	96%	96%
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 (CSM) predictors.

The table presents the CSM predictors analyzed in our study. Column (1) lists the original papers, while Column (2) indicates the year each predictor becomes available. Column (3) reports the average number of firms per month with predictor values. The last two columns show the equal-weighted (EW) and value-weighted (VW) fractions of our stock universe — defined as stocks with prices above $5 and market capitalizations above the 20th percentile NYSE cutoff—that have predictor values.

predictors available during that period: industry momentum, BEA-customer, and BEA-supplier predictors. When a predictor becomes available but has missing values for certain stocks, we fill in zeros, which correspond to the cross-sectional mean of uniform distributions ranging from -0.5 to 0.5. As more predictors become available, the combined predictor incorporates a growing number of inputs.

The advantage of this approach lies in its simplicity and transparency. However, one potential concern is that it may not represent an optimal weighting of individual predictors. To address this, we also construct an alternative combined predictor using multivariate return-predicting regressions, where each predictor is weighted based on its relative contribution to return prediction. Appendix A.4 details this regression-based combination procedure. We find that the regression-combined predictor exhibits a 95% rank correlation with our simple average-based predictor. Therefore, unsurprisingly, all our results remain robust to this alternative method.

2.2 Cross-stock momentum reverses

As discussed in the introduction, if CSM returns are entirely driven by underreaction to cash flows, these returns should not revert on average (Samuelson, 1965). The typical method for constructing *dynamically rebalanced* CSM portfolios does not facilitate testing for reversals. To examine whether reversals occur, we need to track the subsequent returns of the *same* portfolios over several years following their initial formation.

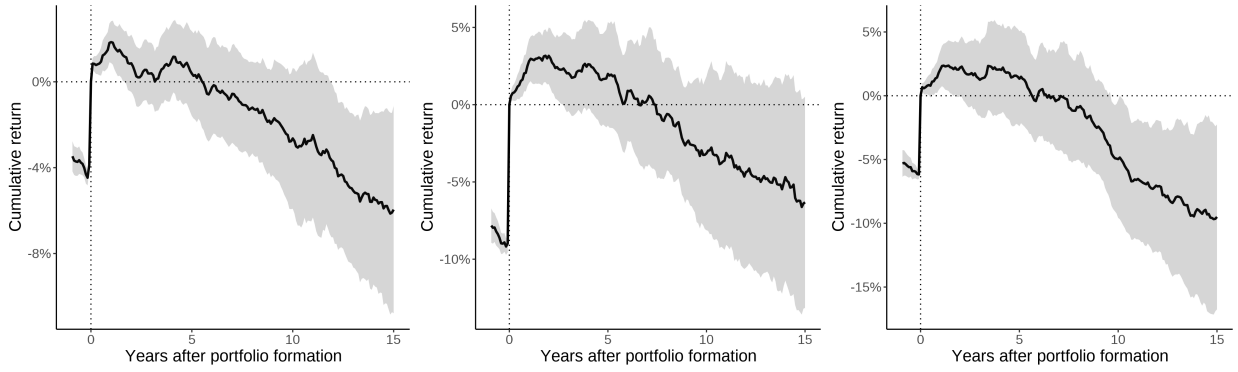
To examine long-horizon returns, in each portfolio formation month (or "vintage") t, we sort stocks into NYSE deciles using a given CSM predictor $s_{i,t}$. For each decile $d = 1, .., 10$ and each horizon $h = 1, ..., H$, we compute value-weighted portfolio returns of $r^p_{d,t+h|t} = \sum_{i \in d} w_{i,t+h-1} \cdot r_{i,t+h}$ where $w_{i,t+h-1}$ are portfolio weights based on lagged market capitalization and $r_{i,t}$ is the return of stock i in month t. Then, for each vintage t, the per-period and cumulative returns to the CSM-sorted long-short decile portfolio is given by, respectively,

$$\text{ret}_{t+h|t} = r^p_{10,t+h|t} - r^p_{1,t+h|t}, \text{ and} \tag{2}$$

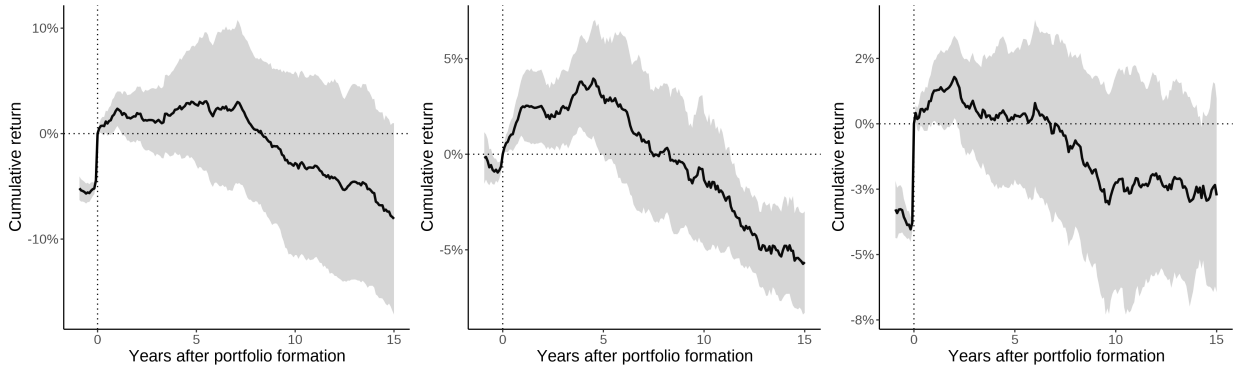
$$\text{cumret}_{t+1 \to t+h|t} = \prod_{s=1}^{h} (1 + \text{ret}_{t+s|t}) - 1 \tag{3}$$

For portfolios formed using the combined CSM predictor, we plot the average cumulative returns from Equation (3) by horizon h in Panel (a) of Figure 1. The shaded areas represent 95% confidence intervals, computed using the Newey-West procedure with the same number of lags as the horizon h. Consistent with previous literature, we observe positive returns in the short term, with cumulative returns of two to three percent within one year of portfolio formation. However, we also find that these returns reverse in the subsequent period, a result not previously documented in the literature.

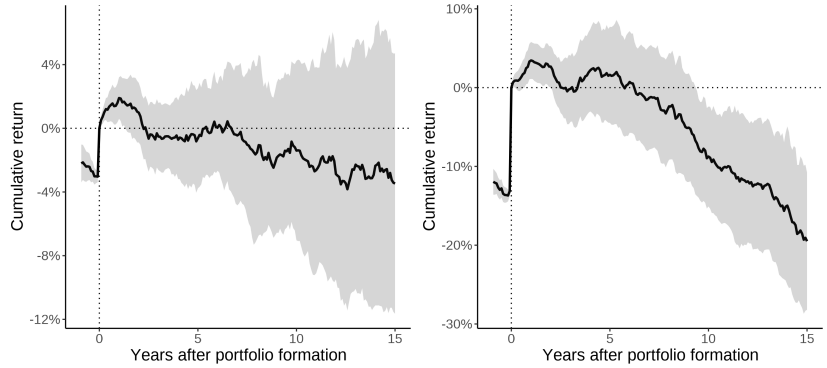
This reversal is not specific to the combined predictor but holds for all individual CSM predictors. Figure 2 plots the cumulative post-formation portfolio returns for each individual



(a) Industry momentum (b) BEA customer (c) BEA supplier



(d) Technology link (e) Geographic link (f) Complicated firms



(g) Economic link (h) Analyst coverage

Figure 2. Cross-stock momentum reversals: individual predictors

This figure plots the cumulative value-weighted long-short decile returns, with portfolios formed by sorting on individual CSM predictors. The shaded areas represent 95% Newey-West confidence intervals. The predictors are ordered by the time at which they become available.

predictor, and reversals are observed in all cases. Although there is variation in the magnitude of the reversals, the point estimates indicate full reversal of the initial CSM returns after five to ten years for all predictors.

	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	0.93***	2.34***	−5.87**	−4.71***	−7.57***	(0.14)	(0.54)	(2.50)	(1.64)	(2.61)
Industry momentum	0.85***	1.85***	−5.95**	−4.17**	−7.33***	(0.13)	(0.49)	(2.41)	(1.69)	(2.49)
BEA customer	0.56***	2.81***	−6.32*	−5.28**	−8.22***	(0.17)	(0.70)	(3.42)	(2.05)	(3.00)
BEA supplier	0.67***	2.07***	−9.50***	−5.89***	−9.85***	(0.16)	(0.73)	(3.62)	(2.03)	(3.15)
Technology link	0.50**	2.36***	−8.08*	−4.66	−9.74**	(0.20)	(0.82)	(4.54)	(3.87)	(4.09)
Geographic link	0.35***	2.50***	−5.64***	−3.51*	−8.10***	(0.13)	(0.81)	(1.33)	(1.87)	(1.02)
Complicated firms	0.41***	1.27**	−2.74	−3.25**	−3.94**	(0.14)	(0.58)	(1.85)	(1.62)	(1.57)
Economic link	0.51***	1.90***	−3.47	−3.48	−5.51	(0.15)	(0.65)	(4.09)	(2.76)	(3.71)
Analyst coverage	0.67**	3.45***	−19.49***	−10.37***	−19.61***	(0.29)	(1.17)	(4.35)	(3.45)	(4.96)

Table 2. Returns of cross-stock momentum portfolios.

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

The reversal is statistically significant for the combined CSM predictor and most individual predictors. Table 2 reports the average cumulative returns for different event periods after portfolio formation, along with Newey-West standard errors. Specifically, a column labeled (m, n) represents the cumulative return from month m (inclusive) to month n after portfolio formation. Columns (1) and (2) show that all portfolios exhibit positive long-short returns at the 1- and 12-month horizons at the 5% significance level. To examine reversals, columns (4) and (5) report returns for 10- and 15-year horizons, excluding the most recent year. The combined predictor shows a statistically significant reversal for both horizons. For the individual predictors, the point estimates are all negative, with reversals statistically significant at the 5% level for five (seven) out of eight predictors at the 10- and 15-year horizons, respectively.

Detecting long-horizon return reversals is typically challenging with slow-moving return predictors. However, our situation is different. CSM, by its nature, is a fast-moving return predictor, as each portfolio is formed using the most recent monthly returns. Since there is limited time-series correlation in monthly returns, consecutive CSM portfolios formed in

months t and $t+1$ are quite distinct. As a result, the correlation between $\text{cumret}_{t+1\to t+h|t}$ and $\text{cumret}_{t+2\to t+h+1|t+1}$ is low, around 0.1 (see Appendix A.2). This characteristic of CSM provides more statistical power to our empirical exercise.

There is a conceptual correspondence between our findings and those of Lee and Swaminathan (2000) and Jegadeesh and Titman (2001). To explore the nature of stock momentum, they find that stock momentum reverses over time, which contradicts explanations that only contain underreaction. Similarly, our finding that CSM reverses over time suggests that the entire effect cannot be attributed to underreaction to cash flow information.

Robustness. Our finding of CSM reversal is robust to several alternative specifications. We summarize these robustness checks here and present details in the Appendix.

1. **Alternative delisting treatments.** When a firm delists in month $t+h$, we assume that it earns the delisting return in that month, and the remaining value is reinvested into the other stocks starting from month $t+h+1$. For delisting returns, we use the values reported in CRSP when available. If the delisting return is not available in CRSP, we follow the literature by using -55% for NASDAQ stocks and -30% for other stocks (Shumway, 1997; Shumway and Warther, 1999).

   Appendix A.1 demonstrates that our finding of return reversal is robust to alternative approaches to handling delistings (e.g. Hou et al., 2020). Additionally, we observe that the fraction of stocks that delist is quite similar between the long and short legs of CSM portfolios, suggesting that our results are unlikely to be driven by delisting firms. Specifically, on a value-weighted (equal-weighted) basis, approximately 78% (54%) of stocks in both legs survive after 15 years, implying that roughly 1.5% (3.1%) of firms delist each year on a value-weighted (equal-weighted) basis.
2. **Bootstrapped standard errors.** In addition to using Newey-West standard errors, we also compute block bootstrapped standard errors and find broadly similar results. Our bootstrap perserves the time-series correlations both within vintage and across

vintages. Appendix A.2 presents these results and explains why our study exhibits higher statistical power compared to typical studies on long-horizon return predictions.

3. **Alternative portfolio constructions.** In Appendix A.3, we report that our results are robust to alternative portfolio constructions, including using equal-weighted portfolios or long-short quintile (instead of decile) portfolios. In all specifications, we find statistically significant evidence that CSM reverses.

2.3 Cross-stock momentum as a "build-up" anomaly

In Panel (a) of Figure 1, we find that the eventual return reversal is larger than the initial CSM momentum. This result is statistically significant, as shown in column (3) of Table 2. For the combined CSM predictor, the cumulative 15-year return after portfolio formation is -5.87%, which is statistically significantly negative at the 5% confidence level. For the individual CSM predictors, the point estimates are all negative, with four out of eight being statistically significant at the 5% level using Newey-West standard errors. When using bootstrapped standard errors (as seen in Table A1), the coefficient is statistically negative at the 1% confidence level for the combined predictor and six out of eight individual predictors.

It is natural to ask how the reversal could be stronger than the initial returns. A significant part of the answer lies in the returns during the portfolio formation period. In Figures 1 and 2, we depart from previous studies by plotting the returns up to one year before portfolio formation. As the plots indicate, there is considerable price movement in the portfolio formation month, which is unsurprising given that the CSM portfolio is formed by sorting on peer stock returns. To the extent that peer and focal stock returns are correlated, we would expect a large contemporaneous movement in the focal stocks as well. Therefore, our reversal results suggest that a substantial part of the sorting-period return also reverses over time.

What do we learn from the fact that reversals are larger than initial returns? If CSM-

linked returns reflect rational discount rate changes, we cannot speak of pricing "efficiency." However, if CSM is an anomaly, as most of the CSM literature suggests, this finding implies that the initial CSM returns exacerbate pre-existing price deviations. In other words, stocks in the long CSM portfolio are already "overpriced" relative to those in the short leg, and the initial CSM returns worsen the price deviation before it corrects through subsequent reversals. This differs from the underreaction interpretation, where initial CSM returns are seen as prices reverting to equilibrium levels.

To restate our finding in the language of Van Binsbergen et al. (2023), CSM appears to be a "build-up" anomaly rather than a "resolution" anomaly. Van Binsbergen et al. (2023) argue that most anomalies are of the latter type, where returns represent convergence towards long-run equilibrium, with only a small subset — such as momentum and profitability — being of the former type. We find CSM to be another example of a build-up anomaly. In Sections 3 and 4, we demonstrate that this is linked to the fact that CSM includes a component related to factor momentum, which is also linked to stock momentum.

Our results thus far are based on cumulative returns, which are related to but distinct from results based on price levels (Van Binsbergen et al., 2023; Cho and Polk, 2023). In Appendix A.5, we analyze CSM using the methodology and data from Van Binsbergen et al. (2023). They develop a method to measure the degree to which price levels deviate from long-run equilibrium. Results based on their approach are qualitatively consistent with ours and also indicate that CSM returns represent the exacerbation of pre-existing price deviations.

3 Decomposing Cross-Stock Momentum

In this section, we aim to understand why cross-stock momentum (CSM) exhibits long-run reversals. While CSM findings are often framed in terms of *unidirectional* lead-lag relationships (e.g., peer stock leading focal stock), Burt and Hrdlicka (2021) argues that such

lead-lag relationships can also arise from momentum in common components. Specifically, peer and focal stocks may load onto common factors that themselves exhibit momentum. Following this reasoning, we first demonstrate that a significant portion of CSM reflects common movements between peer and focal firms, and then show that the common component accounts for the entire reversal. We then propose a methodology to remove the common component.

3.1 Common momentum and reversals: preliminary evidence

For a preliminary examination of the idea that CSM may contain common components, we study the peer portfolios alongside the focal portfolios. Recall that for a given CSM predictor, each focal stock i is connected to a peer portfolio with weights $\{\Pi_{i,j}\}_{j=1}^{N}$. Then, for a focal portfolio with weights $\{w_i^{\text{focal}}\}_{i=1}^{N}$, the corresponding peer portfolio has portfolio weights of $\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_i^{\text{focal}}\cdot\Pi_{i,j}}{\sum_i w_i^{\text{focal}}}$ in each stock j.



Figure 3. Peer versus focal portfolios

We compute value-weighted long-short decile portfolio returns for both focal and peer stocks sorted on cross-stock momentum (CSM) predictors. The figure plots the cumulative post-formation returns for these two portfolios using the combined CSM predictor, with shaded areas representing 95% Newey-West confidence intervals.

Figure 3 plots the cumulative return of long-short peer portfolios alongside the focal portfolios for the combined CSM predictor. Interestingly, we observe similar momentum and reversal patterns in the peer portfolios, indicating that these patterns arise from common components. While we only plot the results for the combined CSM predictor, Appendix A.6 finds broadly similar results for all individual CSM predictors.

3.2 Separating unidirectional lead-lags and common components

Motivated by the previous subsection, which finds that much of the reversal is due to common components, we now aim to remove these common components from CSM. To do this, we follow the approach proposed by Yan and Yu (2023), which decomposes CSM into "symmetric" and "asymmetric" components. The "symmetric" component captures common factor movements,[2] while the "asymmetric" component reflects unidirectional lead-lag relationships, as desired.

We briefly describe their methodology and provide intuition for interpreting these two components. Yan and Yu (2023) observe that all CSM predictors take the following form:

$$s_t = \Pi \cdot r_t$$

where s_t is the N-vector of predictors, Π is an $N \times N$ "prediction matrix," and r_t is the N-vector of stock returns. CSM effects correspond to being able to use s_t to predict r_{t+1}. We note that the rows of Π are simply the peer portfolio weights.[3] Under this formulation,

[2] We use the term "factor" synonymously with "portfolio," following the factor momentum literature. This is a statistical description, and we make no claims about whether such factors represent economic risks or mispricings.

[3] For instance, consider industry momentum. For each focal stock i, the predictor is $s_{i,t} = \sum_j \Pi_{i,j} \cdot r_{j,t}$ where the peer weights are given by:

$$\Pi_{i,j} = \begin{cases} \frac{M_{j,t}}{\sum_{k \in \text{ind}(i)} M_{k,t}} & \text{if } \text{ind}(j) = \text{ind}(i) \\ 0 & \text{if } \text{ind}(j) \neq \text{ind}(i) \end{cases}$$

where $M_{j,t}$ is the market cap and $\text{ind}(k)$ denotes the industry that stock k belongs to.

the prediction matrix, as well as the predictor, can be additively decomposed into symmetric and asymmetric components:

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

$$s_t = \underbrace{\Pi_{\text{sym}} \cdot r_t}_{=s_t^{\text{sym}}} + \underbrace{\Pi_{\text{asy}} \cdot r_t}_{=s_t^{\text{asy}}} \tag{5}$$

Because Π_{asy} is skew-symmetric ($\Pi_{\text{asy},i,j} = -\Pi_{\text{asy},j,i}$), by construction, it captures unidirectional lead-lag relationships. In contrast, Yan and Yu (2023) show that the symmetric component captures common factor momentum, which we explain further in Appendix B.1. We now provide intuition for this decomposition using a two-asset example.

A two-asset example. We consider two CSM predictors and illustrate how the symmetric and asymmetric components capture the common and undirectional effects.

1. **A symmetric case.** Suppose the CSM predictor is characterized by the following relationship

$$\underbrace{E_t \begin{bmatrix} r_{1,t+1} \\ r_{2,t+1} \end{bmatrix}}_{=E_t(r_{t+1})} = \underbrace{\begin{bmatrix} 0.1 & 0.1 \\ 0.1 & 0.1 \end{bmatrix}}_{=\Pi} \cdot \underbrace{\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix}}_{=r_t}.$$

   It should be intuitive that there is no unidirectional lead-lag. Rather, the predictive relationship is characterized by momentum in a common component shared by the two stocks. Consistent with this intuition, the entire prediction matrix is attributed to the

symmetric part:

$$\Pi_{\text{sym}} = \frac{\Pi + \Pi'}{2} = \begin{bmatrix} 0.1 & 0.1 \\ 0.1 & 0.1 \end{bmatrix}$$
$$\Pi_{\text{asy}} = \frac{\Pi - \Pi'}{2} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}.$$

Further, a principal component analysis of Π_{sym} gives

$$\Pi_{\text{sym}} = \underbrace{\begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}}_{W} \cdot \underbrace{\begin{bmatrix} 0.2 & 0 \\ 0 & 0 \end{bmatrix}}_{\Lambda} \cdot \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ -1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}}_{W'},$$

which indicates that the return predictability is fully characterized by momentum in the factor portfolio that has equal weights stocks 1 and 2 (the first column of W).

2. **A case with unidirectional lead-lags.** Consider a slightly different prediction matrix of

$$\Pi = \begin{bmatrix} 0.1 & 0.1 \\ 0 & 0.1 \end{bmatrix}.$$

Intuitively, this example contains both common and unidirectional lead-lag components. Stock 2 should lead stock 1 to some extent, as $r_{2,t}$ matters for predicting $r_{1,t+1}$, but $r_{1,t}$ does not matter in predicting $r_{2,t+1}$. Consistent with intuition, the decompo-

sition yields

$$\Pi_{\text{sym}} = \begin{bmatrix} 0.1 & 0.05 \\ 0.05 & 0.1 \end{bmatrix}$$
$$\Pi_{\text{asy}} = \begin{bmatrix} 0 & 0.05 \\ -0.05 & 0 \end{bmatrix},$$

where the asymmetric component captures a unidirectional lead-lag relationship from stock 2 to 1 in the off-diagonal elements.

3.3 The common component accounts for the reversal

We now apply the symmetric-asymmetric decomposition to all individual CSM predictors. For the combined predictor, we construct its symmetric and asymmetric components using the procedure described in Section 2.1, averaging over the corresponding components of the individual predictors.[4]

Before examining expected returns, we first assess the correlation of *realized* returns between peer and focal portfolios to check whether the symmetric component indeed captures common components. Table 3 reports the correlation between long-short decile portfolios formed using focal and peer firms in the 15 years after portfolio formation. The first row examines the combined CSM predictor and shows a high correlation of 0.71 between the focal portfolio based on the original ("total") CSM predictor and the peer portfolio. The second column reports a correlation of 0.45 between the symmetric component and the peer portfolio. Column (3) shows that the correlation disappears when using the asymmetric component. The subsequent rows report results for individual CSM predictors, revealing broadly similar patterns. Overall, the symmetric component appears to capture common

[4]Specifically, we first convert each individual symmetric (asymmetric) predictor into a uniform distribution over [-0.5, 0.5] using cross-sectional ranks, and then take the average over them to obtain the combined symmetric (asymmetric) CSM predictor.

components.

Predictor	Return correlation		
	Total	Symmetric	Asymmetric
	(1)	(2)	(3)
Combined predictor	0.71	0.45	-0.03
Industry momentum	0.74	0.41	-0.05
BEA customer	0.76	0.36	-0.10
BEA supplier	0.68	0.34	-0.02
Technology link	0.78	0.72	-0.21
Geographic link	0.54	0.50	0.12
Complicated firms	0.23	0.39	-0.02
Economic link	0.23	0.13	-0.05
Analyst coverage	0.91	0.81	-0.37
Average	0.61	0.46	-0.09

Table 3. Return correlations of peer and focal portfolios

As described in Section 3.1, we form long-short decile portfolios based on peer CSM firms. The table reports the correlation of realized returns between the focal and peer portfolios in the 15 years following portfolio formation. Column (1) presents the results when the focal portfolio is formed using the entire CSM predictor, while columns (2) and (3) show the results using only the symmetric and asymmetric components of the predictor, respectively. The first row considers the combined CSM predictor. The subsequent eight rows examine each individual predictor, and the last row reports the average across all individual predictors.

We then proceed to study expected returns. Panel (b) of Figure 1 plots the cumulative return of the value-weighted long-short NYSE decile portfolios for the combined symmetric and asymmetric CSM predictors, respectively. As shown in the graph, the reversal occurs exclusively in the symmetric component. Appendix Figure A3 finds broadly similar patterns in the individual CSM predictors. This suggests that the symmetric-asymmetric decomposition approach is successful in isolating the common component

To facilitate a more detailed comparison between the two components, we report their average portfolio returns in Table 4. The first observation is that the symmetric component accounts for more variation in expected returns. In the first three rows, which examine the full sample, we see that using the total CSM predictor, the associated long-short portfolio delivers a 1.04% return in the first month, strengthening to 2.65% by twelve months. The point estimates in the second row show that the symmetric component accounts for more than half of the first-month return and around three-quarters of the twelve-month return. In contrast, the

asymmetric component delivers 0.39% in the first month, with no statistically significant evidence of further returns beyond the first month. The subsequent rows examine subsamples where we split the full sample by the year of 1962 when many stock characteristics become available. The results are qualitatively similar across subsamples.

		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	1.04***	2.65***	−6.41***	−4.77***	−8.46***	(0.14)	(0.60)	(2.14)	(1.58)	(2.08)
	Symmetric	0.63***	1.97***	−5.70**	−3.31*	−7.41***	(0.12)	(0.52)	(2.51)	(1.97)	(2.53)
	Asymmetric	0.39***	0.51	2.10	−0.03	1.48	(0.10)	(0.51)	(2.54)	(2.19)	(2.46)
1926-1962	Total	1.03***	2.04**	−3.17	−3.97*	−5.23**	(0.25)	(0.89)	(2.30)	(2.37)	(2.28)
	Symmetric	0.77***	1.67**	−4.04*	−4.09	−5.67**	(0.19)	(0.71)	(2.11)	(2.72)	(2.25)
	Asymmetric	0.23	0.35	1.10	0.03	0.65	(0.19)	(0.92)	(1.26)	(2.52)	(1.04)
1963-2023	Total	1.05***	3.03***	−9.01***	−5.35***	−11.06***	(0.17)	(0.79)	(2.42)	(2.04)	(2.18)
	Symmetric	0.54***	2.16***	−7.03*	−2.75	−8.81**	(0.15)	(0.72)	(3.95)	(2.63)	(3.90)
	Asymmetric	0.48***	0.61	2.90	−0.07	2.16	(0.11)	(0.60)	(4.36)	(3.15)	(4.12)

Table 4. Returns of decomposed cross-stock momentum (CSM) portfolios

This table reports post-formation returns of value-weighted long-short NYSE decile portfolios sorted on the combined CSM predictor. "Total" refers to sorting on the original CSM predictor, while "symmetric" and "asymmetric" refer to sorting on the subcomponents of the predictor. The column name (m, n) refers to cumulative returns from month $t+m$ to $t+n$, where t is the portfolio formation month. The first three rows examine the full sample, and the next six rows examine two subsamples. The first five columns report returns in percentage terms, and the last five columns report Newey-West standard errors. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

More importantly, the reversal occurs exclusively in the symmetric component. As shown in column (5) of Table 4, after skipping the first post-portfolio formation year, the symmetric component exhibits statistically significant reversals at the 15-year horizon, with a magnitude similar to that of the original CSM portfolio. In contrast, there is no evidence of reversals in the asymmetric component, a result that holds in both subsamples.

4 Interpreting Decomposed Components

How should we interpret the common and unidirectional lead-lag components of cross-stock momentum (CSM)? In this section, we argue that the latter aligns more closely with the traditional underreaction explanation, as its returns materialize within approximately one

month of portfolio formation, do not revert, and are weaker in stocks with higher liquidity. In contrast, the common component, as discussed in Section 3.2, represents a form of factor momentum. While it is not fully captured by the specific factor momentum implementation of Arnott et al. (2023), the two are correlated and share similar features, including 12-month momentum and long-run reversals. Although factor momentum may partly reflect underreaction, its eventual reversal and susceptibility to alternative explanations make it difficult to attribute solely to underreaction. Therefore, researchers seeking to isolate the underreaction-driven component of CSM should focus on the unidirectional lead-lag effects.

4.1 The unidirectional lead-lag component

This section shows that the asymmetric component of CSM is more pronounced in stocks with lower liquidity. This is consistent with the idea that it reflects underreaction-based mispricing, which arbitrageurs attempt to exploit but are constrained by trading costs.

We proxy liquidity using the negative of bid-ask spreads. To maximize sample coverage, we use bid-ask spread estimates from Corwin and Schultz (2012), derived from daily high and low prices, which extend back to the beginning of the CRSP dataset. To reduce measurement noise, we compute bid-ask spreads in month t using an exponentially smoothed average of the past twelve months $(t-12, ..., t-1)$, with exponential weights calibrated through forecasting regressions. The implied half-life of these weights is approximately one month. Our findings are robust to using raw bid-ask spreads instead.

To obtain a more complete picture of how CSM returns vary with liquidity, we now include all stocks in CRSP, including those below the 20% NYSE size cutoff that were previously excluded. We partition the sample into five bins based on the liquidity measure, using breakpoints at the 5%, 20%, 50%, and 80% NYSE cutoffs. Within each bin, we compute long-short value-weighted decile portfolio returns by cross-sectionally sorting stocks. The resulting monthly returns are presented in Table 5.

	Bin1	Bin2	Bin3	Bin4	Bin5	Bin 1-3	Bin 3-5	Bin 1-5
Panel A: combined predictor								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	1.85***	1.55***	0.97***	0.91***	0.93***	0.88*	0.04	0.92**
	(0.45)	(0.25)	(0.17)	(0.14)	(0.13)	(0.45)	(0.16)	(0.46)
Symmetric	0.81*	0.74***	0.80***	0.43***	0.48***	0.01	0.32**	0.33
	(0.43)	(0.23)	(0.15)	(0.13)	(0.12)	(0.43)	(0.15)	(0.43)
Asymmetric	1.84***	0.83***	0.59***	0.31***	0.17	1.25***	0.42***	1.67***
	(0.45)	(0.22)	(0.16)	(0.12)	(0.12)	(0.44)	(0.16)	(0.47)
Panel B: individual predictors, asymmetric component								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry momentum	1.83***	0.73***	0.36**	0.22*	0.13	1.47***	0.23	1.70***
	(0.45)	(0.23)	(0.16)	(0.12)	(0.11)	(0.43)	(0.16)	(0.46)
BEA customer	1.47***	0.55***	0.42***	0.32**	0.26**	1.05***	0.16	1.21***
	(0.28)	(0.20)	(0.15)	(0.13)	(0.13)	(0.30)	(0.17)	(0.30)
BEA supplier	1.39***	0.46**	0.41**	0.29**	0.31**	0.99***	0.10	1.09***
	(0.27)	(0.20)	(0.16)	(0.14)	(0.13)	(0.29)	(0.18)	(0.29)
Technology link	0.25	0.13	0.19	0.27	0.27	0.07	−0.08	−0.01
	(0.33)	(0.26)	(0.20)	(0.17)	(0.17)	(0.39)	(0.25)	(0.36)
Geographic link	0.36	0.12	0.43**	0.29*	0.13	−0.07	0.30	0.23
	(0.30)	(0.24)	(0.20)	(0.17)	(0.16)	(0.34)	(0.25)	(0.33)
Complicated firms	0.70**	0.23	−0.07	0.53***	0.25*	0.77***	−0.31	0.45
	(0.28)	(0.22)	(0.16)	(0.15)	(0.15)	(0.29)	(0.20)	(0.31)
Economic link	0.58	0.28	0.41**	−0.14	0.02	0.17	0.39	0.56
	(0.45)	(0.26)	(0.19)	(0.16)	(0.16)	(0.48)	(0.24)	(0.48)
Analyst coverage	1.37***	0.73***	−0.02	0.23	−0.02	1.39***	−0.00	1.39***
	(0.35)	(0.26)	(0.23)	(0.18)	(0.17)	(0.43)	(0.24)	(0.38)

Table 5. Return predictability by stock liquidity

We sort the full CRSP sample cross-sectionally into five bins based on liquidity, measured as the negative of the bid-ask spread. These bins correspond to stocks with liquidity in the $< 5\%, 5$–$20\%, 20$–$50\%, 50$–80%, and $> 80\%$ ranges, using NYSE breakpoints. The table presents average monthly long-short value-weighted decile returns in percentage terms. Panel A reports results for the combined CSM predictor, including its original ("total"), symmetric, and asymmetric components. Panel B focuses on the asymmetric component of individual CSM predictors. Columns (1)–(5) show average returns for each bin, while columns (6)–(8) present pairwise differences between selected bins. Standard errors are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Panel A analyzes the combined CSM predictor, considering both the original ("total") predictor and its symmetric and asymmetric components separately. We find that the profitability of the asymmetric component is strongly linked to liquidity. Its monthly return reaches 1.84% in the first bin, which contains the most illiquid stocks, but declines sharply to below 1% in the second bin and continues to decrease monotonically as liquidity increases. In the most liquid stocks (above the 80% NYSE cutoff), returns become statistically insignificant. Columns (6) through (8) confirm that these differences are statistically significant across

bins. In contrast, the symmetric component remains profitable even in the most liquid stocks, suggesting that its return pattern is less dependent on liquidity.

Panel B presents the returns of the asymmetric components for individual CSM predictors. Among the four predictors with sizeable asymmetric returns — industry momentum, BEA customer, BEA supplier, and analyst coverage — all exhibit a similar dependence on liquidity. Their returns exceed 1% in the most illiquid stocks but are significantly smaller in the most liquid bin. For the other four predictors, their asymmetric components do not generate strong returns, making it difficult to detect an interaction with liquidity. Overall, we conclude that the profitability of the asymmetric component of CSM tends to be stronger in illiquid stocks.

4.2 Relationship with factor and stock momentum

In Section 3.2, we argue that the symmetric component of CSM represents a form of factor momentum, where the factors correspond to the principal component portfolios of the symmetric prediction matrix. This suggests a potential link between CSM and the factor momentum (FM) documented by Arnott et al. (2023), which finds that characteristics-sorted factors exhibit momentum. If this connection holds, our findings imply that FM may also experience reversals.

This section provides suggestive evidence for this view. We show that CSM, FM, and a stock-level momentum (MOM) strategy based on sorting one-month raw returns display similar momentum and subsequent reversals. Spanning tests indicate that FM and MOM explain part of CSM's initial momentum and a significant portion of its long-term reversals.

Factor construction. We construct a simplified version of FM following the "cross-sectional factor momentum" methodology of Arnott et al. (2023). Their approach selects a set of long-short, characteristics-based factors and dynamically rebalances by going long (short) in the top (bottom) half of factors based on recent monthly performance. They show

that this strategy earns excess returns.

Following their methodology, we construct a simplified version of their strategy using factors derived from the characteristics listed in Appendix B.2. While Arnott et al. (2023) analyze only one-month post-formation performance, we extend the study to examine FM's long-run post-formation returns, mirroring our approach with CSM.[5]

Since our sample begins before many characteristics become available, the FM strategy initially relies only on price-based characteristics, a small subset of the factors in Arnott et al. (2023). As a result, our construction may omit significant factor variation. To address this, we also construct an alternative version by sorting stocks based on raw month-t returns, forming a value-weighted long-short NYSE decile portfolio, which we denote as MOM, akin to stock momentum. Unlike the (t-12, t-1) momentum in Jegadeesh and Titman (1993), this strategy sorts solely on one-month returns. However, by examining long-term return predictability post-formation, we argue that it captures similar lead-lag effects in stock returns.

We first observe that CSM, FM, and MOM — each constructed based on sorting stocks by some version of one-month returns — are highly correlated. Specifically, for one-month

[5]In each portfolio formation month t and for each factor $k = 1, , , ., K$, we first sort stocks by the corresponding characteristic into deciles $D^k_{1,t}, ..., D^k_{10,t}$. We obtain the portfoilo weight of each stock i in this factor as:

$$w^k_{i,t} = \begin{cases} -\frac{w_{i,t}}{\sum_{j \in D^k_{1,t}} w_{j,t}} & \text{for decile 1} \\ 0 & \text{for deciles } 2, ..., 9 \\ \frac{w_{i,t}}{\sum_{j \in D^k_{10,t}} w_{j,t}} & \text{for decile 10} \end{cases}.$$

To target their version of FM, we further aggregate the stock-level weights as:

$$w_{i,t} = \frac{1}{K/2} \sum_{k \in \text{Long}_t} w^k_{i,t} - \frac{1}{K/2} \sum_{k \in \text{Short}_t} w^k_{i,t}$$

where Long_t and Short_t are the top and bottom half sets of factors based on their period t returns, respectively. Finally, for any horizon h, we compute the FM factor return as:

$$\text{ret}^{\text{FM}}_{t+h|t} = \sum_i w_{i,t} \cdot r_{i,t+h}.$$

Note that $\text{ret}^{\text{FM}}_{t+1|t}$ is the return studied in Arnott et al. (2023). Our innovation is to also examine longer horizons $h > 1$.

post-formation returns, CSM exhibits correlations of 0.62 with FM and 0.64 with MOM, while FM and MOM have a correlation of 0.69.

Consistent with our intuition, all three factors display similar momentum and reversal patterns following portfolio formation. Figure 4 illustrates their post-formation returns, showing strong momentum within the first 12 months, followed by long-term reversals.[6]

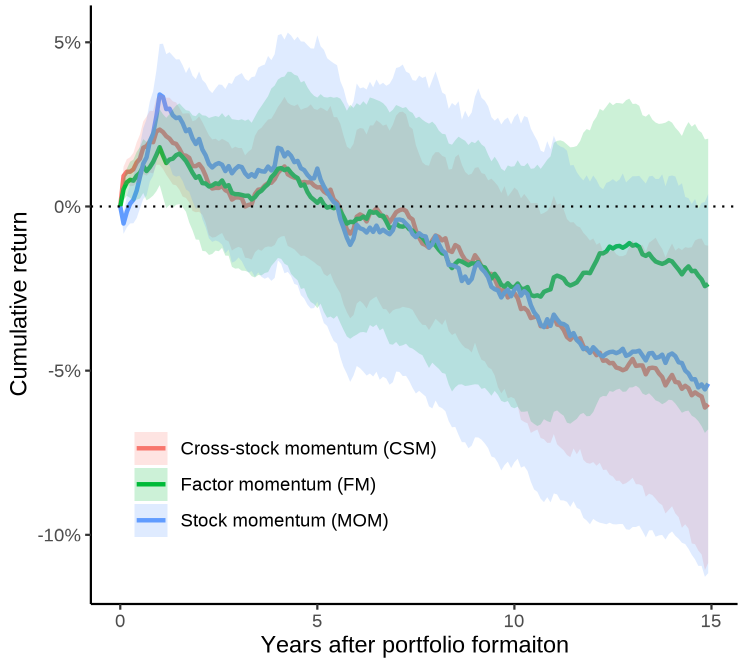


Figure 4. Post-portfolio formation return of different portfolios

We plot the cumulative post-portfolio formation returns of cross-stock momentum (CSM), factor momentum (FM), and stock momentum (MOM). The shaded areas are 95% Newey-West standard errors.

Spanning regressions. We assess the extent to which FM and MOM explain the momentum and reversal patterns in CSM using spanning regressions. The first two columns of Table **??** focus on one-month post-formation returns. Over the sample period where all factor data are available, CSM earns a monthly return of 0.929%, with FM accounting for approximately one-third of this magnitude. We do not control for MOM at this horizon due to its short-term reversal effects.

[6]Due to the well-documented short-term reversal effect, our MOM construction experiences reversals within the first month.

Next, we analyze long-term reversals. Columns (3)–(6) examine cumulative 15-year post-formation returns, excluding the first year. Column (3) shows that CSM reverses by 7.763% on average, while column (4) indicates that FM explains only a small portion of this reversal. In contrast, column (5) demonstrates that MOM has greater explanatory power, reducing the intercept by more than half. Column (6) further confirms that, once MOM is accounted for, FM's additional explanatory power is minimal.

Dependent variable: CSM return (in %)						
	$t+1$		$t+13 \to t+180$			
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.929^{***}	0.623^{***}	-7.763^{***}	-6.379^{***}	-3.554	-3.659^{*}
	(0.14)	(0.11)	(2.55)	(2.08)	(2.31)	(2.13)
FM		0.581^{***}		0.375^{***}		0.154^{*}
		(0.02)		(0.08)		(0.08)
MOM					0.495^{***}	0.416^{***}
					(0.06)	(0.06)
Obs	1,174	1,174	996	996	996	996
Adj R^2	0.00%	38.16%	0.00%	13.49%	24.38%	25.98%

Table 6. CSM spanning regressions

We conduct time-series regressions of CSM factor returns on contemporaneous FM and MOM factor returns. The first two specifications analyze one-month post-formation returns, while the last four focus on cumulative 15-year returns, excluding the first year. Newey-West standard errors are reported in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Overall, these results support the notion that CSM incorporates a component resembling factor momentum, which tends to reverse over time. Our findings also align with earlier observations of factor and stock momentum, though the phenomena are not identical.

4.3 Alternative approaches to control for common components

Thus far, we have used the symmetric-asymmetric decomposition to control for common components in CSM returns. In this section, we explore an alternative approach inspired by Burt and Hrdlicka (2021). We demonstrate that, in the limit, their method closely aligns with ours. Additionally, we confirm that our key conclusion — that approximately half of CSM returns stem from common components — remains robust under this alternative framework.

Before introducing their approach, we first quantify the fraction of CSM returns attributable to the residual (asymmetric) component based on our symmetric-asymmetric decomposition. Panel A of Table 7 presents long-short decile portfolio returns using either the original CSM predictor (first row) or its residual asymmetric component (second row), with the third row reporting the ratio between the two. The results indicate that at the one-month horizon, 35% of CSM returns can be attributed to the residual component, with a delta method-based standard error of 12%. As the horizon extends, this fraction declines further, stabilizing at approximately one-sixth and also becomes statistically insignificant.[7] Panel B examines the post-1963 sample and finds similar results: at the one-month horizon, the residual asymmetric component accounts for roughly half of CSM returns, with its contribution decreasing over longer horizons.

Method	Horizon (m):	Cumulative returns (%)					Standard error (%)				
		1	2	3	6	12	1	2	3	6	12
		Panel A: full sample, 1926 - 2023									
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sym/asy	Total	0.93***	1.06***	1.06***	1.46***	2.34***	(0.14)	(0.19)	(0.22)	(0.37)	(0.54)
	Residual	0.32***	0.40***	0.27	0.19	0.35	(0.10)	(0.15)	(0.20)	(0.35)	(0.54)
	Ratio	35%***	38%**	26%	13%	15%	(12%)	(16%)	(20%)	(24%)	(23%)
		Panel B: later sample, 1963 - 2023									
Sym/asy	Total	0.85***	0.96***	0.95***	1.42***	2.64***	(0.17)	(0.25)	(0.29)	(0.48)	(0.73)
	Residual	0.45***	0.29	0.23	0.29	0.48	(0.12)	(0.19)	(0.24)	(0.40)	(0.61)
	Ratio	52%***	30%	24%	21%	18%	(17%)	(21%)	(26%)	(29%)	(23%)
Regression	Total	0.85***	0.96***	0.95***	1.42***	2.64***	(0.17)	(0.25)	(0.29)	(0.48)	(0.73)
	Residual	0.42***	0.55***	0.53***	0.74***	1.40***	(0.10)	(0.14)	(0.15)	(0.23)	(0.39)
	Ratio	49%***	57%***	56%***	52%***	53%***	(13%)	(18%)	(21%)	(19%)	(16%)

Table 7. Fraction of cross-stock momentum not due to common components

For the combined CSM predictor, we compute the fraction of returns attributed to the residual component, excluding common factor movements. This table reports results based on long-short NYSE value-weighted decile portfolios. Panel A examines the full sample, showing the 1-, 2-, 3-, 6-, and 12-month post-portfolio formation returns for portfolios based on the original CSM predictor ("Total") and the residual asymmetric component ("Residual"). The last row in Panel A reports the ratio of average returns between the "Residual" and "Total" portfolios. Panel B examines the sample starting from 1963 and includes a regression-based approach to compute residual portfolios following Burt and Hrdlicka (2021). The first five columns in both panels report point estimates, and the last five columns show Newey-West standard errors, using the delta method when necessary. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

[7]For horizons beyond one month, we compute return covariances using sufficient lags to account for overlapping sample periods. This covariance matrix is then used to compute the standard error for the "Ratio" row via the delta method.

An alternative method to control for common components. Burt and Hrdlicka (2021) (henceforth BH) proposes an alternative methodology where the researcher explicitly specifies the common factors to be controlled. They first decompose stock returns in the portfolio-formation period into a factor-based component and residuals

$$r_{i,t} = a_t + \sum_{k=1}^{K} b_{i,k} \cdot f_{k,t} + r_{i,t}^{\text{resid}}, \tag{6}$$

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 use the residual $r_{i,t}^{\text{resid}}$ to construct the CSM predictor, $s_t^{\text{resid}} = \Pi \cdot r_t^{\text{resid}}$, which is then used to predict subsequent stock returns, and the predictability is interpreted as the non-common (non-factor) component.

The key difference between their methodology and ours lies in how common factors are controlled for. Our approach extracts common factors directly from the prediction matrix, and we control for *all* such factors, including latent ones. In contrast, the BH approach requires the researcher to specify the factors to control for. This introduces a risk of undercontrolling if the researcher is unaware of all relevant factors. However, if all relevant factors are known, the BH approach should yield results similar to ours. In Appendix B.2, we show that as the number of controlled factors increases, results based on the BH methodology converge toward ours. Therefore, our methodology is more comprehensive, automatically controlling for common factors without requiring additional input from the researcher.

The BH methodology also offers its own advantages. It enables researchers to attribute effects to interpretable factors, a feature not afforded by our approach. Additionally, it is well-suited for researchers who have economically-motivated reasons to select specific factors for control. Overall, we do not take a definitive stance on which methodology is more appropriate, and we present results based on the BH method as a robustness check.

We implement the BH methodology by controlling for the Fama-French 12 industries and

a set of commonly used characteristics-based factors: accruals, asset growth, beta, book-to-market, gross profitability, 1- and 5-year net issuances, non-operating assets, realized volatility, size, stock momentum, intermediate momentum, and seasonal momentum. In each period, we run cross-sectional regressions of stock returns on rank-transformed regressors (Equation (6)) to obtain return residuals, which are then used to construct CSM predictors. Appendix B.2 provides implementation details. Due to the requirement for stock characteristics data, this methodology can only be applied to the post-1963 sample.

In the last three rows of Table 7, for the "Residual" row, we report returns of the long-short portfolio formed using the BH-residualized CSM predictor ($s_t^{\text{resid}} = \Pi \cdot r_t^{\text{resid}}$). At the one-month horizon, the results are similar to those using the symmetric-asymmetric decomposition and suggest that around half of the CSM returns are unrelated to common factor movements. At longer horizons, a larger fraction of the returns is attributed to the residual component, supporting the notion that the BH methodology controls only for user-specified factors, whereas the symmetric-asymmetric approach accounts for hidden factors as well.

5 International Cross-Stock Momentum

In this section, we conduct an out-of-sample test by applying our symmetric-asymmetric decomposition method to CSM in international markets. Unlike the U.S. market, only two types of CSM predictors — industry momentum and the analyst coverage-based CSM from Ali and Hirshleifer (2020) — can be easily computed in many countries. We examine these for a broader set of markets and find evidence that international CSM returns also revert, and that the reversal is driven by the symmetric components.

5.1 Data

We use monthly global stock returns and characteristics data from WRDS, as provided by Jensen et al. (2023), and apply their recommended data filters. For industry momentum, we use the Fama-French 49 industries classification, also provided by them. To measure analyst coverage, we merge return data with the IBES detailed file and follow Ali and Hirshleifer (2020) by using the occurrence of 1- and 2-year earnings forecasts in the past 12 months to infer coverage patterns. To exclude the most illiquid stocks, we remove those below 1% of NYSE market capitalization, referred to as "nano" stocks in Jensen et al. (2023).

We select markets with sufficient data. For industry momentum, a market is included once it has at least 100 stocks, and we require this number to never dip below 50 thereafter. We include all markets starting by 2000 and having data through 2023. For the analyst CSM predictor, we follow the market and start date selection criteria from Ali and Hirshleifer (2020). All subsequent analyses follow the same procedure used for the U.S. market, except we use raw, rather than NYSE, breakpoints when forming decile portfolios.

Table 8 summarizes the markets included in our study, with 23 markets for industry momentum and 10 for analyst coverage. We report the average number of stocks, as well as the time-series averages of the fraction of stock value accounted for by each market. Japan (JPN) is the largest market, accounting for around 30% of both CSM predictors, followed by Great Britain (GBR). Markets in the industry momentum sample have start years ranging from 1987 to 1999, while the start years for the analyst coverage predictor range from 1989 to 1997, following Ali and Hirshleifer (2020).

5.2 Results

Panel (a) of Figure 5 plots the one-month long-short value-weighted decile returns of the industry momentum CSM by market. The red lines represent returns based on the original CSM predictor ("Total"), with the shaded areas indicating 95% confidence intervals. The

Panel A: Industry momentum				Panel B: Analyst coverage CSM			
Market	Sample period	Firms	Fraction	Market	Sample period	Firms	Fraction
	(1)	(2)	(3)		(4)	(5)	(6)
CAN	1987 - 2023	295	5.9%	GBR	1989 - 2023	784	19.4%
GBR	1988 - 2023	836	14.3%	JPN	1989 - 2023	1,314	33.9%
JPN	1988 - 2023	2,164	29.8%	DEU	1990 - 2023	289	9.3%
AUS	1989 - 2023	432	3.5%	FRA	1990 - 2023	311	11.5%
DEU	1989 - 2023	356	6.2%	HKG	1993 - 2023	408	9.0%
FRA	1989 - 2023	381	7.7%	CHE	1995 - 2023	147	5.0%
MYS	1992 - 2023	349	1.2%	NLD	1995 - 2023	97	2.9%
HKG	1994 - 2023	819	5.8%	SWE	1996 - 2023	178	2.3%
ITA	1994 - 2023	197	2.3%	ESP	1997 - 2023	96	3.2%
SGP	1994 - 2023	282	1.3%	ITA	1997 - 2023	160	3.4%
THA	1994 - 2023	274	0.8%				
CHE	1995 - 2023	187	3.5%				
NLD	1995 - 2023	104	2.2%				
ESP	1996 - 2023	121	2.1%				
SWE	1996 - 2023	238	1.6%				
DNK	1997 - 2023	96	0.7%				
IDN	1997 - 2023	216	0.6%				
IND	1997 - 2023	696	3.1%				
KOR	1997 - 2023	882	2.4%				
TWN	1997 - 2023	836	2.4%				
ZAF	1997 - 2023	163	1.0%				
NOR	1998 - 2023	140	0.6%				
BEL	1999 - 2023	101	0.8%				

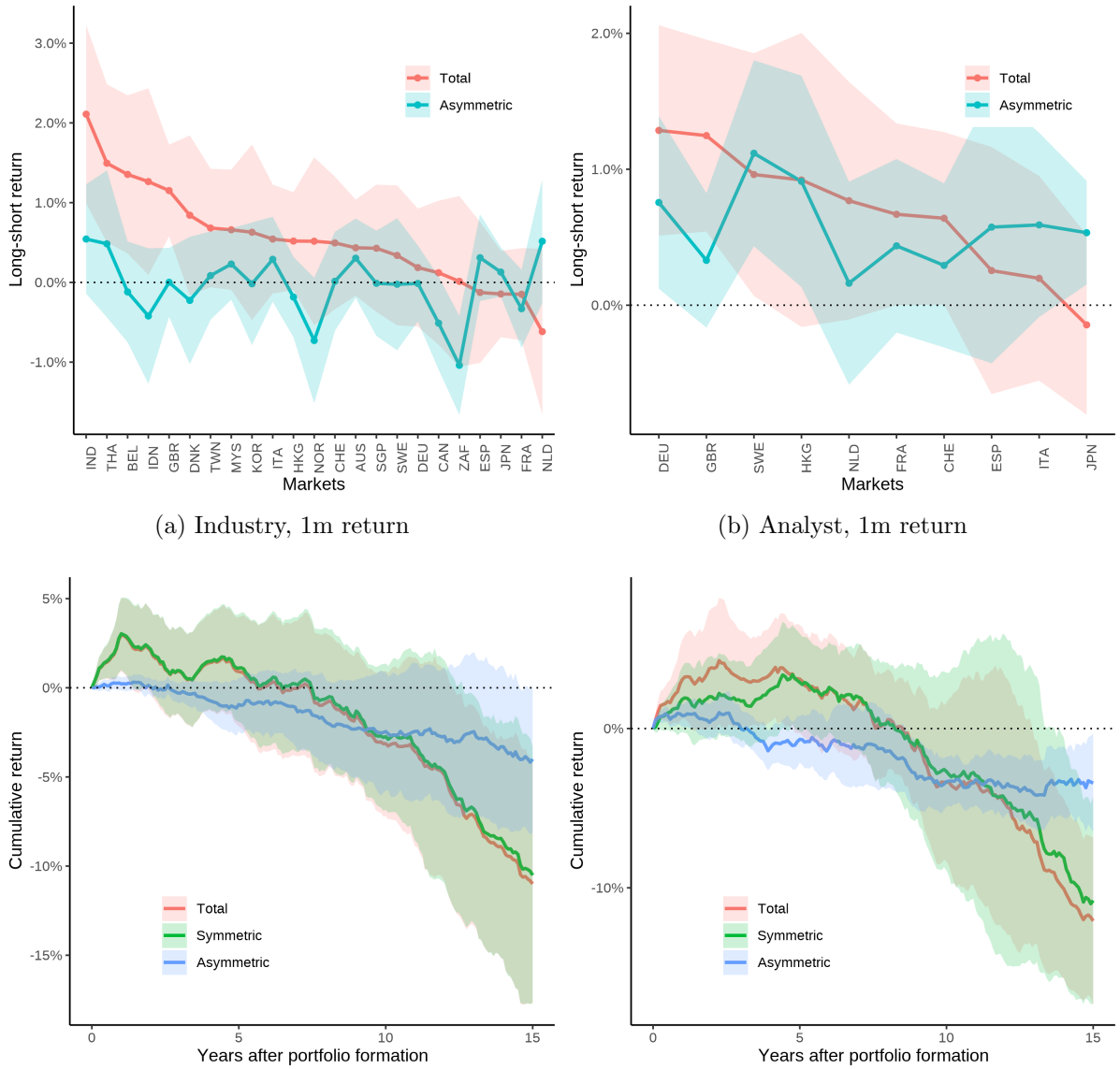
Table 8. International sample

The table presents the markets used in constructing international CSM. The sample excludes stocks with market capitalization below the 1% NYSE cutoff. Panel A lists the markets for industry momentum, while Panel B lists those for the analyst coverage CSM. For both panels, we report the sample period, the average number of stocks per month, and the value-weighted fraction of the market. For industry momentum, each market's start date is defined as the first time the market has 100 stocks. For the analyst coverage CSM, we use the same start dates as in Ali and Hirshleifer (2020).

markets are ranked in descending order of returns. Out of 23 markets, 19 show positive returns, with 5 statistically significant at the 5% level. The blue lines represent returns for the asymmetric component of CSM. Notably, the returns are centered around zero, with only 11 out of 23 markets showing positive point estimates, and none statistically significant at the 5% level. These results suggest that industry momentum in international markets is primarily driven by common factor movements.

In contrast, the analyst coverage predictor, shown in Panel (b), exhibits significant asymmetric components. Using the original CSM predictor, 9 out of 10 markets have positive point estimates, with 5 statistically significant at the 5% level (DEU, GBR, SWE, FRA, and CHE). When focusing on the asymmetric component, all 10 markets show positive point estimates, with 4 statistically significant (DEU, SWE, HKG, and JPN).

Section 3 finds that the symmetric component of CSM reverses in the U.S. market. Is this also true in international markets? To address this, we examine long-horizon cumulative returns to long-short portfolios in international markets. Given the limited data in many international markets compared to the U.S., we pool all markets together to increase statistical power, weighting each market by its share of total market capitalization (columns (3) and (6) in Table 8). We compute Driscoll-Kraay standard errors to account for both time-series and cross-sectional correlations across countries. The results, plotted in Panels (c) and (d) of Figure 5, show largely similar patterns: CSM returns revert, with the reversal primarily attributed to the symmetric component.



(a) Industry, 1m return

(b) Analyst, 1m return

(c) Industry, cumulative return

(d) Analyst, cumulative return

Figure 5. Decomposing international cross-stock momentum

We study industry momentum and analyst coverage CSM in international markets. Panels (a) and (b) display the average one-month returns of long-short value-weighted portfolios for the total and asymmetric components by market, with 95% Newey-West confidence intervals shaded. Panels (c) and (d) present the cumulative returns after portfolio formation, estimated by pooling markets together and weighting them by their market capitalization. The shaded areas represent 95% confidence intervals based on Driscoll-Kraay standard errors.

6 Conclusion

The study of cross-stock momentum (CSM) has garnered significant attention in the literature, with researchers documenting various patterns in which the returns of peer stocks

can predict the returns of connected focal stocks. These findings are often interpreted as evidence of underreaction to cash flow news. However, if underreaction were the sole explanation, CSM returns should not revert (Samuelson, 1965). In contrast, we find that many prominent CSM returns reverse over longer horizons, suggesting a more complex underlying mechanism. Moreover, the magnitude of the eventual reversal exceeds the initial momentum, indicating that CSM returns represent prices diverging further from, rather than converging towards, long-run equilibrium price levels.

To explain these reversals, we note that a significant portion of CSM does not simply reflect unidirectional lead-lag relationships but also arises from common factor components exhibiting momentum and reversals. We use an analytical identity to decompose CSM into two components: a symmetric component capturing common factors and an asymmetric component reflecting unidirectional lead-lag relationships. Our analysis shows that the symmetric component accounts for part of the initial momentum while fully explaining the subsequent reversals. This common component is related to factor momentum and is not necessarily indicative of underreaction. In contrast, the asymmetric component, which accounts for roughly one-third to half of the initial CSM returns, appears more consistent with the traditional underreaction explanation. Our findings suggest a nuanced interpretation of CSM, and we recommend that future research focus on the unidirectional lead-lag components when quantifying the influence of underreaction.

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A Additional Empirical Results

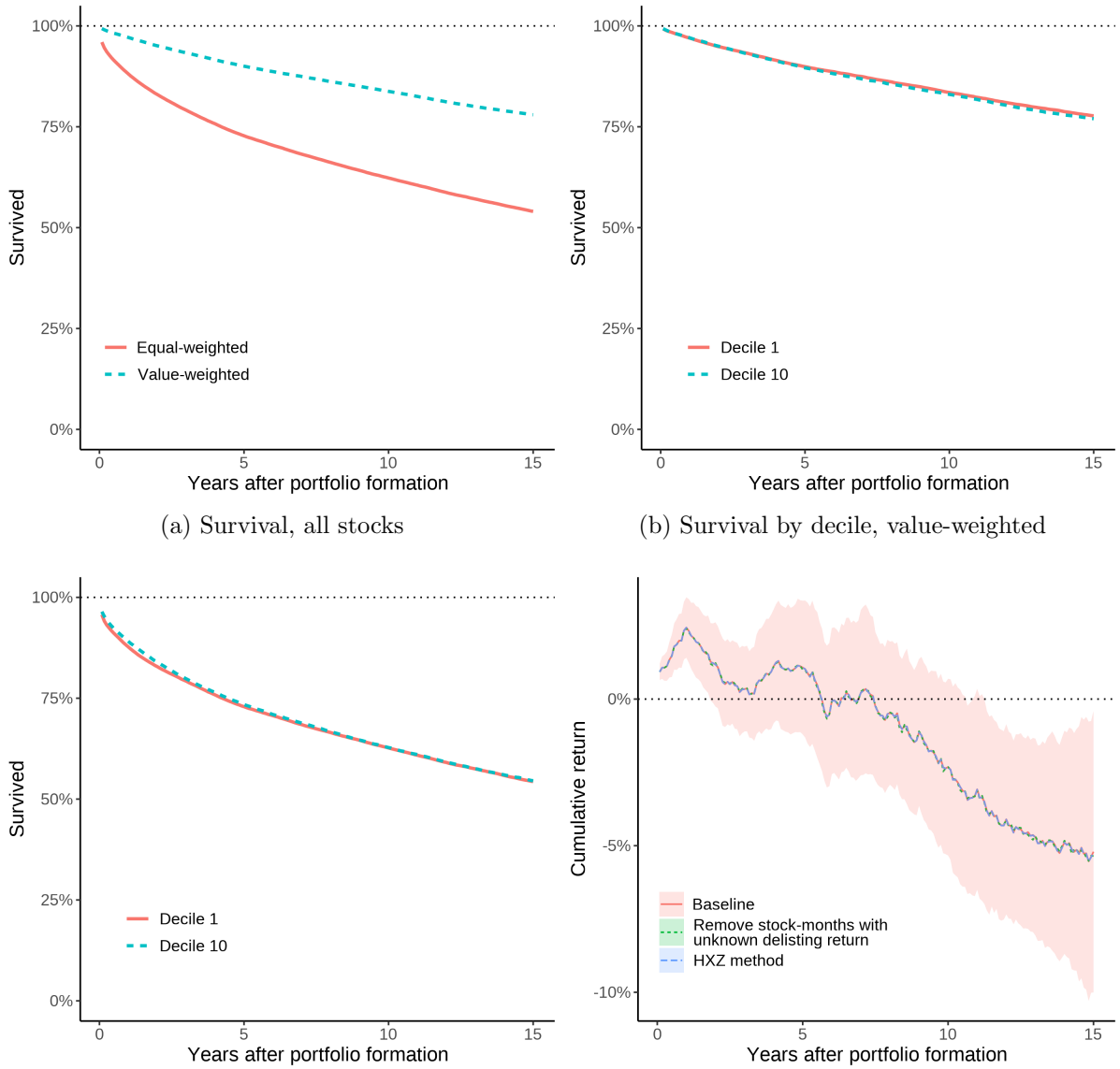
A.1 Delisting

Since our results in Section 2.2 examine long-horizon performance of portfolios after formation, there is concern that delisting stocks over time might drive the observed reversals. In this section, we address this concern by providing evidence that delistings are unlikely to explain the reversals. We find that the fraction of delisted stocks is very similar between the long and short portfolios, suggesting that differential delisting rates do not contribute to the long-term reversal pattern we document. Furthermore, our main results are robust to alternative delisting treatments.

We present the results in Figure A1. Panel (a) plots the cumulative fraction of stocks that survived (i.e., did not delist) by horizon after portfolio formation. On an equal-weighted basis, approximately 54% of stocks survive for 15 years. On a value-weighted basis, which is more relevant for our analysis based on value-weighted portfolios, approximately 78% of stocks survive for 15 years. Panels (b) and (c) plot the survival rates for the combined CSM predictor-sorted long and short decile portfolios, showing that the survival rates are fairly balanced across these portfolios. In unreported tests, we also find that survival rates are similar for deciles 2 through 9, but we omit these results from the graph to avoid overplotting. Therefore, our findings based on long-short portfolios are unlikely to be significantly affected by delisting rates.

In Panel (d), we recompute the cumulative long-short value-weighted returns from Figure 1 Panel (a) using alternative delisting return treatments. The red line reproduces our baseline result. As discussed in Section 2.2, when CRSP lacks delisting returns, we follow the literature by making assumptions about delisting returns.[8] To test the robustness of our assumptions, the green dotted line shows the results if our long-short portfolio rotates out of stocks with missing delisting returns one month before delisting, thereby eliminating the need to assume delisting returns. The blue dashed line follows the methodology in Hou et al. (2020), where missing delisting returns are imputed using returns from similar stocks in recent periods. All results remain highly similar under these alternative approaches, indicating that our findings are not sensitive to delisting treatment. While not reported for brevity, we also find that alternative delisting treatments do not impact our results for any of 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 delisting returns. This is partly due to our restriction of attention to stocks above the 20% NYSE market capitalization cutoff, as larger stocks are less likely to have missing delisting returns.



(a) Survival, all stocks

(b) Survival by decile, value-weighted

(c) Survival by decile, equal-weighted

(d) Cumulative return

Figure A1. Investigating the effect of delisting

This figure examines the potential impact of stock delisting after portfolio formation on the main results presented in Panel (a) of Figure 1. Panel (a) plots the cumulative fraction of stocks that survive (i.e., did not delist) over time. Panels (b) and (c) show the value- and equal-weighted survival rates for the long and short decile portfolios, respectively. Panel (d) displays the cumulative long-short portfolio returns under alternative delisting return treatments. The red line represents the baseline results under our main specification. The green dotted line excludes stock-months with unknown delisting returns, assuming the trading strategy rebalances out of delisting stocks one month prior to delisting. The blue dashed line follows the delisting treatment outlined in Hou et al. (2020). The shaded areas represent 95% confidence intervals for the baseline results.

individual CSM predictors.

A.2 Bootstrapped standard errors

The main paper computes Newey-West standard errors when inferring long-horizon cumulative returns post-portfolio formation. For robustness, in this section, we compute block-bootstrapped standard errors. We first describe the bootstrap procedure and the rationale behind our choices, then present the results.

Bootstrap procedure. For a given CSM predictor, we observe $T \times H$ return realizations of long-short portfolio returns $\{\{\text{ret}t+h|t\}\}h = 1^{H}{}_{t=1}^{T}$, where t represents the vintage (portfolio formation period) and h is the forecasting horizon. We are interested in computing standard errors for cumulative returns over horizons m to n, with the point estimate given by:

$$\hat{\mu}_{m,n} = \frac{1}{T}\sum_{t=1}^{T} \text{cumret}_{t+m\to t+n|t},$$
$$\text{where } \text{cumret}_{t+m\to t+n|t} = \prod_{h=m}^{n}(1+\text{ret}_{t+h|t}) - 1$$

In designing the bootstrap, we first want to preserve the within-vintage time-series relationships to capture the momentum and reversals. Therefore, for each bootstrap repetition, we resample vintages $\{v_1, ..., v_T\}$ from the original vintages $\{1, ..., T\}$ and set the returns as:

$$\text{ret}^{\text{boot}}_{t+h|t} = \text{ret}_{v_t+h|v_t}.$$

Second, we want to preserve across-vintage dependence, as CSM portfolios formed in subsequent periods may be correlated. Thus, we cannot resample vintages independently from $\{1, ..., T\}$. Instead, we conduct a block bootstrap with length B, so that each consecutive block of B bootstrapped vintages corresponds to a consecutive block in the original data.[9] If vintage t is the beginning of a block, we would have:

$$\begin{aligned}
\text{ret}^{\text{boot}}_{t+h|t} &= \text{ret}_{v_t+h|v_t} \\
\text{ret}^{\text{boot}}_{t+h+1|t+1} &= \text{ret}_{v_t+h+1|v_t+1} \\
&\vdots \\
\text{ret}^{\text{boot}}_{t+h+B|t+B} &= \text{ret}_{v_t+h+B|v_t+B}
\end{aligned}$$

[9] That is, after sampling v_1 from $\{1, ..., T\}$, the subsequent $B-1$ bootstrapped vintages are set to be $v_1 + 1, ..., v_B$, before resampling v_{B+1} independently from $\{1, ..., T\}$ with replacement.

for all $h = 1, ..., H$.

How large should we set the block length B? This depends on the degree of correlation across vintages, which we can investigate empirically. To do this, we compute the autocorrelation function of $\text{cumret}_{t+1\to t+h|t}$ across vintages t for different forecasting horizons h.[10] In Figure A2, we plot the autocorrelation for horizons $h = 60$, 120, and 180, which correspond to 5, 10, and 15 years, respectively. We estimate autocorrelations for all individual CSM predictors, report the averages, and plot locally estimated non-parametric lines. The results show that, while nearby vintages exhibit moderate correlation (around 0.1), the correlations decay with the number of lags.

Why is the correlation across vintages low, even for forecasting long-horizon returns (e.g., 15 years)? This is because the CSM portfolios are re-formed each month using the most recent monthly returns. As the time-series correlation of monthly returns is low, the portfolio compositions are quite different across vintages.

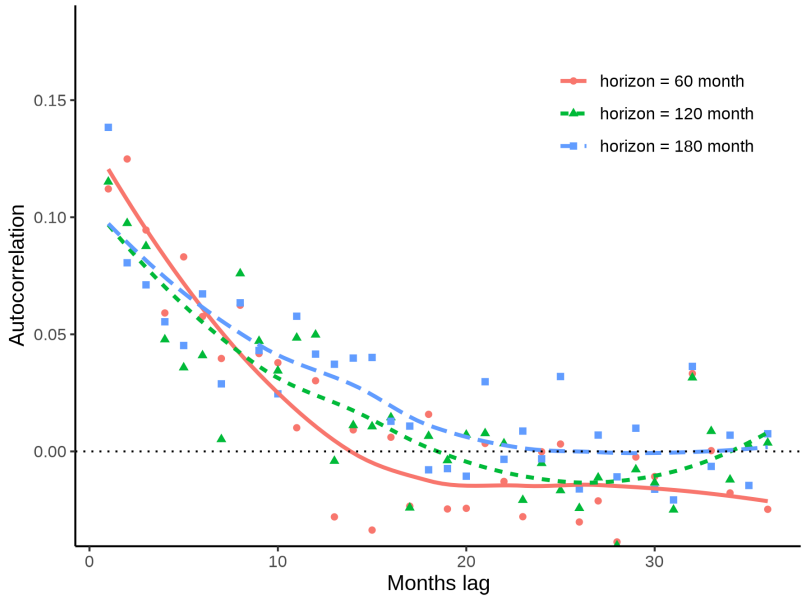


Figure A2. Autocorrelation of cumulative returns across vintages

We plot the autocorrelations for cumulative returns over different forecasting horizons. Specifically, for each forecasting horizon h, we compute $\text{cumret}_{t+1\to t+h|t}$, which is the cumulative h-month return for the long-short portfolio formed in month t. Then, for each h, we compute the autocorrelation over vintages by varying the number of lags (e.g., vintage t vs vintage $t+l$ for lag l) and average the estimate across all CSM predictors. The resulting autocorrelations are plotted as dots, with the lines representing locally smoothed estimates.

If we use the optimal block length estimator in Politis and White (2004), it suggests a block

[10] That is, for each lag $l = 1, ..., 36$, we compute the correlation between $\text{cumret}_{t+1\to t+h|t}$ and $\text{cumret}_{t+l+1\to t+l+h|t+l}$.

length of approximately $B = 3$ months when estimating for the longest forecasting horizon of 15 years. Based on Figure A2, we take a more conservative approach and use a block length of 12 months, at which the autocorrelations appear to fully die out.

Results. Table A1 reports our main results in Table 2 but using bootstrapped standard errors based on 1,000 bootstrap repetitions. The results are qualitatively unaffected, and the key reversal patterns remain statistically significant. While unreported, all the results in our paper are qualitatively unaffected by using block bootstrapped standard errors instead of Newey-West 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	0.93***	2.34***	−5.87***	−4.71***	−7.57***	(0.15)	(0.55)	(1.92)	(1.66)	(1.92)
Industry momentum	0.85***	1.85***	−5.95***	−4.17***	−7.33***	(0.15)	(0.51)	(1.77)	(1.61)	(1.78)
BEA customer	0.56***	2.81***	−6.32***	−5.28**	−8.22***	(0.17)	(0.74)	(2.41)	(2.18)	(2.46)
BEA supplier	0.67***	2.07***	−9.50***	−5.89***	−9.85***	(0.17)	(0.64)	(2.35)	(2.03)	(2.37)
Technology link	0.50***	2.36***	−8.08***	−4.66	−9.74***	(0.18)	(0.87)	(2.94)	(2.90)	(2.86)
Geographic link	0.35***	2.50***	−5.64***	−3.51*	−8.10***	(0.11)	(0.80)	(2.14)	(1.81)	(1.98)
Complicated firms	0.41***	1.27*	−2.74	−3.25*	−3.94*	(0.16)	(0.66)	(2.27)	(1.96)	(2.12)
Economic link	0.51***	1.90**	−3.47	−3.48	−5.51*	(0.14)	(0.79)	(3.35)	(2.31)	(3.24)
Analyst coverage	0.67**	3.45***	−19.49***	−10.37***	−19.61***	(0.30)	(1.22)	(3.14)	(3.16)	(3.13)

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 as described in Appendix A.2.

A.3 Additional details on cross-stock momentum reversal

This section provides additional details supporting our main finding that CSM returns revert. For comparison, Panel A of Table A2 replicates the results from Table 2. Panel B presents results using equal-weighted, rather than value-weighted, portfolios. In Panel C, we report results for value-weighted long-short quintile portfolios, as opposed to deciles. While some variation exists across specifications, the evidence for long-term reversals remains robust.

Section 3 shows that for the combined CSM predictor, the symmetric component is responsible for the reversals. Figure A3 conducts the same exercise for all individual CSM predictors and find qualitatively similar patterns.

A.4 Regression-based combination of CSM predictors

In the main paper, we combine the individual CSM predictors by taking stock-level averages, similar to the approach in Stambaugh and Yuan (2017). While simple, one might be inter-

	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)
Panel A: decile portfolios, value-weighted										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	0.93***	2.34***	−5.87**	−4.71***	−7.57***	(0.14)	(0.54)	(2.50)	(1.64)	(2.61)
Industry momentum	0.85***	1.85***	−5.95**	−4.17**	−7.33***	(0.13)	(0.49)	(2.41)	(1.69)	(2.49)
BEA customer	0.56***	2.81***	−6.32*	−5.28**	−8.22***	(0.17)	(0.70)	(3.42)	(2.05)	(3.00)
BEA supplier	0.67***	2.07***	−9.50***	−5.89***	−9.85***	(0.16)	(0.73)	(3.62)	(2.03)	(3.15)
Technology link	0.50**	2.36***	−8.08*	−4.66	−9.74**	(0.20)	(0.82)	(4.54)	(3.87)	(4.09)
Geographic link	0.35***	2.50***	−5.64***	−3.51*	−8.10***	(0.13)	(0.81)	(1.33)	(1.87)	(1.02)
Complicated firms	0.41***	1.27**	−2.74	−3.25**	−3.94**	(0.14)	(0.58)	(1.85)	(1.62)	(1.57)
Economic link	0.51***	1.90***	−3.47	−3.48	−5.51	(0.15)	(0.65)	(4.09)	(2.76)	(3.71)
Analyst coverage	0.67**	3.45***	−19.49***	−10.37***	−19.61***	(0.29)	(1.17)	(4.35)	(3.45)	(4.96)
Panel B: decile portfolios, equal-weighted										
Combined predictor	1.20***	3.20***	−5.67**	−6.04***	−8.20***	(0.14)	(0.63)	(2.82)	(1.70)	(2.28)
Industry momentum	1.05***	2.05***	−7.30**	−5.23***	−8.79***	(0.12)	(0.55)	(2.84)	(1.74)	(2.31)
BEA customer	0.82***	3.26***	−1.50	−3.48	−4.47	(0.15)	(0.66)	(4.57)	(2.46)	(3.55)
BEA supplier	0.71***	2.38***	−4.07	−4.15*	−5.65*	(0.15)	(0.67)	(3.69)	(2.32)	(3.18)
Technology link	0.77***	3.06***	−5.46*	−3.15	−7.49***	(0.20)	(1.03)	(3.26)	(3.32)	(2.68)
Geographic link	0.48***	2.74***	−4.44**	−3.05	−6.59***	(0.12)	(0.70)	(1.77)	(1.88)	(1.39)
Complicated firms	0.60***	1.94***	1.74	−1.33	−0.63	(0.12)	(0.47)	(1.77)	(0.82)	(1.13)
Economic link	0.51***	1.63***	−3.29***	−3.90***	−5.50***	(0.12)	(0.51)	(0.95)	(0.82)	(0.70)
Analyst coverage	1.18***	5.22***	−16.50***	−7.88**	−17.50***	(0.32)	(1.46)	(2.42)	(3.68)	(1.53)
Panel C: quintile portfolios, value-weighted										
Combined predictor	0.81***	1.97***	−4.56**	−3.84**	−6.30***	(0.12)	(0.46)	(1.86)	(1.50)	(1.92)
Industry momentum	0.72***	1.47***	−4.78***	−3.24**	−6.20***	(0.11)	(0.38)	(1.55)	(1.27)	(1.65)
BEA customer	0.51***	2.10***	−4.80**	−3.83***	−6.47***	(0.13)	(0.57)	(2.18)	(1.22)	(2.03)
BEA supplier	0.55***	1.69***	−8.00***	−3.96***	−8.69***	(0.13)	(0.56)	(2.34)	(1.39)	(1.96)
Technology link	0.55***	2.07***	−5.00	−3.94	−6.58*	(0.16)	(0.67)	(3.90)	(3.27)	(3.52)
Geographic link	0.37***	1.81***	−1.27	−1.31	−3.00***	(0.10)	(0.61)	(1.22)	(1.16)	(0.95)
Complicated firms	0.26**	0.75	−2.51**	−2.57**	−3.81***	(0.11)	(0.46)	(0.98)	(1.29)	(0.77)
Economic link	0.19*	0.75*	−0.19	−0.48	−0.91	(0.11)	(0.40)	(2.78)	(2.18)	(2.56)
Analyst coverage	0.48**	2.20**	−13.14***	−7.33**	−13.99***	(0.23)	(0.85)	(4.07)	(3.25)	(4.49)

Table A2. Robustness of Table 2 to alternative specifications

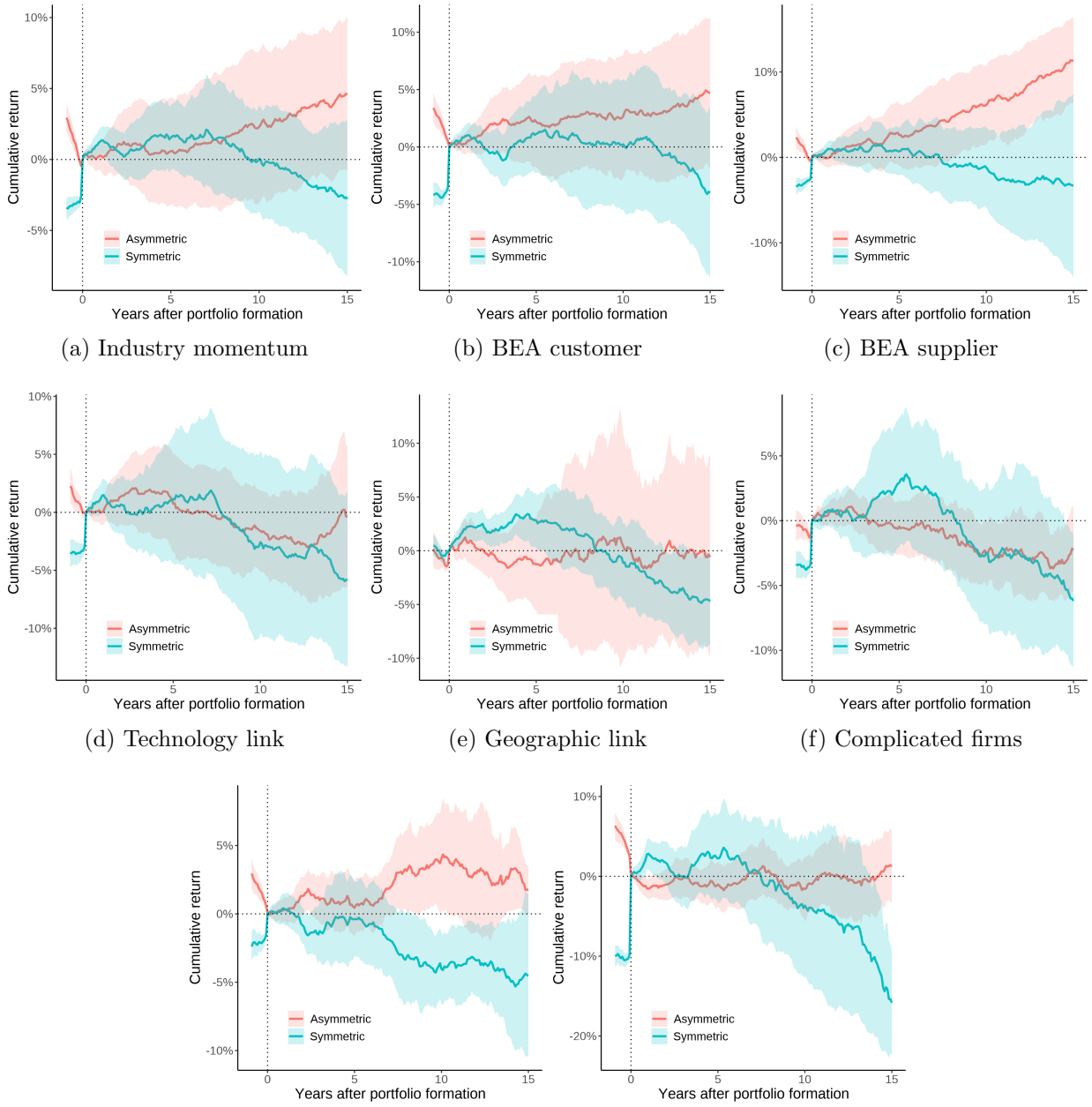
This table assesses the robustness of the results in Table 2, with Panel A reporting the original findings for comparison. Panel B uses equal-weighted portfolios, while Panel C employs value-weighted long-short quintile portfolios instead of deciles.

ested in the results when optimally combining the predictors using a regression framework. In this section, we show that doing so does not materially alter the conclusions of the paper.

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

$$r_{i,t+1} = \sum_{l=1}^{L} b_l \cdot s_{i,t}^l + \tau_t + \epsilon_{i,t+1} \tag{7}$$

where $\{\tau_t\}_{t=1}^T$ are time-fixed effects. We then combine the individual predictors using the



(a) Industry momentum (b) BEA customer (c) BEA supplier

(d) Technology link (e) Geographic link (f) Complicated firms

(g) Economic link (h) Analyst coverage

Figure A3. Cross-stock momentum (CSM) decomposed: individual predictors

This figure plots the cumulative return of value-weighted long-short decile portfolios based on individual CSM predictors, decomposed into symmetric and asymmetric components. The decomposition method is outlined in Section 3.2. Shaded areas represent 95% Newey-West confidence intervals. The predictors are ordered by the time at which they become available.

estimated coefficients,

$$s_{i,t}^{\text{combined}} = \sum_{l=1}^{L} \hat{b}_l \cdot s_{i,t}. \tag{8}$$

The main implementation challenge arises from the staggered availability of the CSM predictors. To construct a complete data panel, we follow the procedure outlined in Berk and Van Binsbergen (2015) to recursively impute the missing predictors using others. Specifically, we begin with the predictor that becomes available last — analyst coverage — which starts in 1983. Using the joint data from 1983 onwards, we estimate a projection of the analyst coverage predictor onto the others, and use this relationship to impute values for the years 1978 to 1982. We then repeat this process for the economic link predictor, which is available from 1978, and continue in this manner. This recursive procedure allows us to impute all predictors, after which we can estimate the regression in Equation (7).

The regression results in column (1) of Table A3 show that all predictors have some explanatory power for future returns. Except for the BEA supplier predictor, all coefficients are statistically significant at the 1% level. Since the predictors are transformed to uniform [-0.5, 0.5] distributions, the coefficients represent the return spread between stocks with the lowest and highest values of each predictor. Columns (2) through (9) present univariate regressions, confirming that each predictor, when considered individually, significantly explains future returns.

	Dependent variable: $r_{i,t+1}$ (in %)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry momentum	0.831***	1.329***							
	(0.10)	(0.15)							
BEA customer	0.423***		1.312***						
	(0.13)		(0.20)						
BEA supplier	0.212			1.117***					
	(0.17)			(0.22)					
Technology link	0.534***				1.339***				
	(0.20)				(0.28)				
Geographic link	0.350***					0.334***			
	(0.09)					(0.09)			
Complicated firms	0.599***						0.574***		
	(0.12)						(0.12)		
Economic link	0.504***							0.875***	
	(0.11)							(0.13)	
Analyst coverage	1.345***								1.996***
	(0.33)								(0.38)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	3,454,299	3,454,299	3,454,299	3,454,299	3,454,299	3,454,299	3,454,299	3,454,299	3,454,299
Within R^2	0.10%	0.05%	0.04%	0.03%	0.01%	0.00%	0.00%	0.01%	0.06%

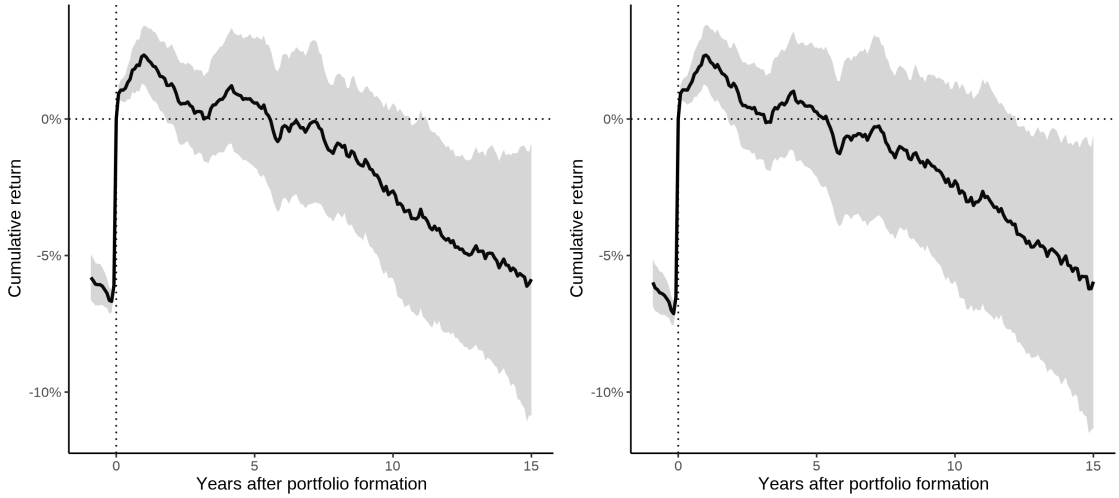
Table A3. Combining predictors using regressions

We estimate panel regressions of next-month stock returns on CSM predictors, which are transformed to uniform [-0.5, 0.5] distributions by ranking within each cross-section. Column (1) includes all predictors, while the remaining columns estimate regressions with one predictor at a time. All specifications control for time fixed effects and cluster standard errors by time and stock. For predictors available only for a subset of the data, we impute missing values through linear projections on the others, as detailed in Appendix A.4. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

We use the point estimates in column (1) of Table A3 to construct the regression-combined CSM predictor, as in Equation (8).

Comparing with the simple combined predictor. The regression-combined predictor is quite similar to the one constructed by averaging predictors in the main paper. The average cross-sectional rank correlation between the two is 0.95, which indicates that they would assign similar stocks to long and short portfolios.

To verify that using these two combined predictors yield highly similar results, we compare cumulative returns returns based on the two combined predictors side-by-side in Figure A4. 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.



(a) Combined predictor, full sample (b) Regression-combined predictor, full sample

Figure A4. 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.

A.5 Price-level analysis

In this section, we conduct a price level analysis on CSM using the methodology and data from Van Binsbergen and Opp (2019). We first briefly describe their methodology before presenting results.

Their price wedge measure. For any stock i, conceptually, one can define its present value justified by future payouts:

$$\tilde{P}_{i,t} = E_t \left(\sum_{s=1}^{J} \frac{m_{t+s}}{m_t} \cdot D_{i,t+s} + \frac{m_{t+J}}{m_t} \cdot P_{i,t+J} \right) \tag{9}$$

where $\{D_{i,t+s}\}_{s=1}^{\infty}$ represent future dividends, $P_{i,t+J}$ is stock price J periods ahead — a long-enough horizon such that mispricings should have mostly dissipated. Van Binsbergen et al. (2023) use $J = 15$ years in their implementation. $\{m_{t+s}\}_{s=1}^{\infty}$ 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 the actual price $P_{i,t}$ from the present value-justified price:

$$PW_{i,t} = \log \left(\frac{P_{i,t}}{\tilde{P}_{i,t}} \right) \tag{10}$$

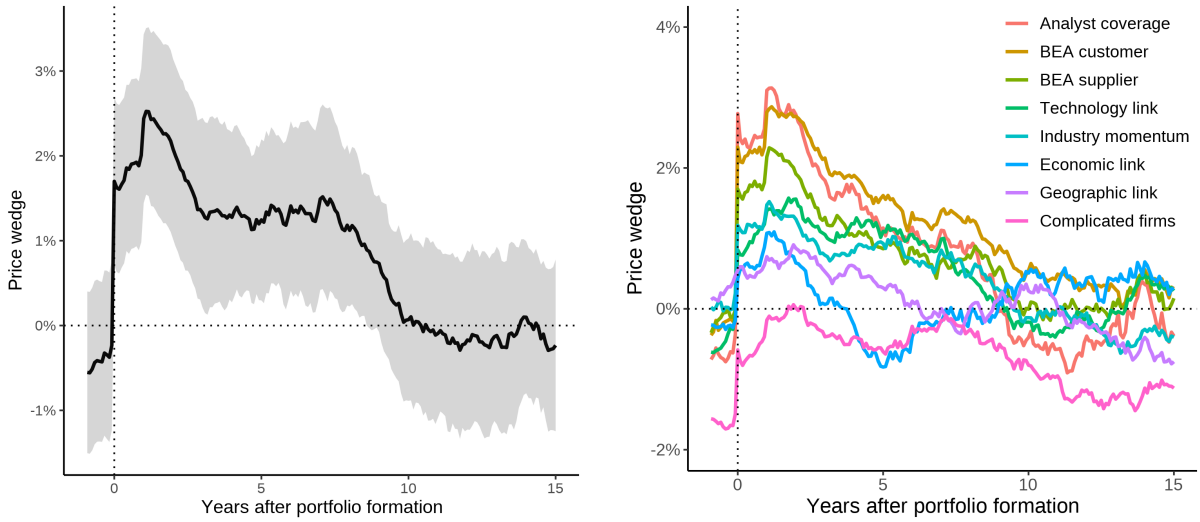
Van Binsbergen et al. (2023) estimated price wedges using a large number of characteristics-sorted portfolios and then projected the price wedges onto individual stocks. This approach ensures that their price wedge measure captures the price deviations associated with the specific set of characteristics they study, but not those that they do not use (e.g., many CSM characteristics). We directly use their stock-level price wedge outputs and merge our data with theirs, which spans from 1964 to 2017.

Price wedge of CSM portfolios. To assess whether CSM represents a build-up anomaly, we compute the value-weighted price wedge of long-short NYSE decile portfolios h months after formation for each portfolio formation month t:

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

Figure A5 shows how the price wedge evolves over different post-formation horizons. Panel (a) displays results for the combined CSM predictor, with the shaded area representing 95% Newey-West confidence intervals. At the formation month, the long portfolio is approximately 2% overvalued relative to the short portfolio. This difference worsens over the next year as CSM returns materialize, before gradually converging to zero in subsequent years.

[11] Panel (b) plots results for individual predictors, showing considerable dispersion but generally supporting the notion that CSMs are build-up anomalies.



(a) Combined CSM predictor

(b) Individual CSM predictors

Figure A5. 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-justified levels — for long-short NYSE decile portfolios sorted on CSM predictors. The evolution of the price wedge is plotted from one year before to 15 years after portfolio formation. Panel (a) shows results for the combined CSM predictor, with shaded areas representing 95% Newey-West confidence intervals. Panel (b) displays results for individual predictors.

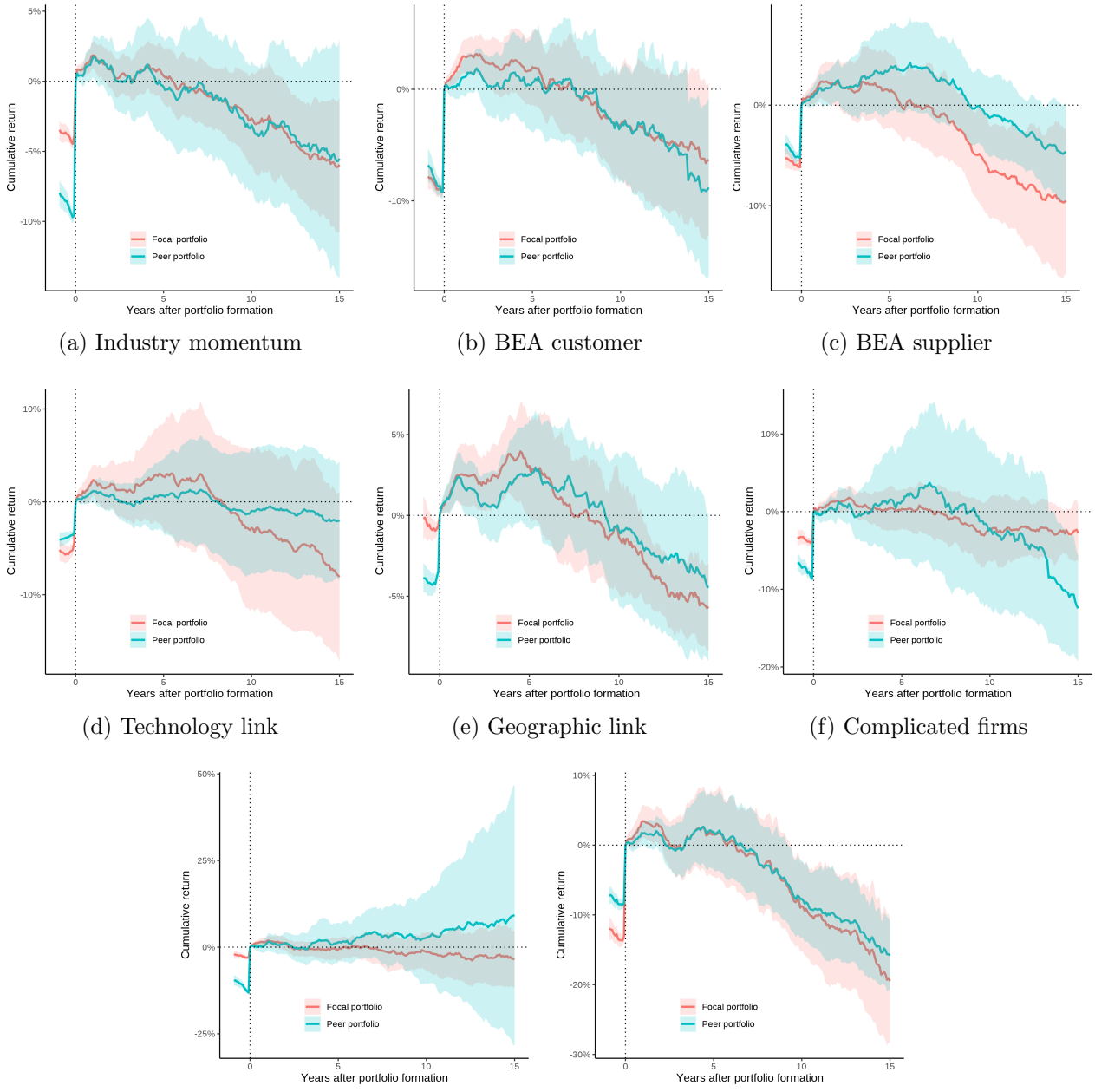
The reader will notice that the magnitude of the price wedge is smaller than the cumulative returns of the CSM portfolios. For example, for the combined CSM predictor, the 12-month post-formation return is 2.34% in Table 2, but only around 1% in Panel (a) of Figure A5. This discrepancy arises because the CSM predictors are not included in the set of characteristics considered by Van Binsbergen et al. (2023), meaning their data captures only a subset of the variation in CSM-sorted portfolios.

A.6 Peer vs. focal plots: all predictors

Figure A6 plots the cumulative returns of long-short peer and focal portfolios for individual CSM predictors. In all cases except the economic link predictor, the results are similar to those in Section 3.1, showing common momentum and reversals in both peer and focal

[11] Although Van Binsbergen et al. (2023) only considers within-15-year return predictability in the price wedge, the convergence of the price wedge is not mechanical. For instance, if a characteristic $x_{i,t}$ predicts returns and $PW_{i,t} = b \cdot x_{i,t}$, where $b > 0$, Figure A5 suggests that, at formation, the long portfolio has higher $x_{i,t}$ than the short portfolio. However, if characteristic differences persist, the price wedge would not converge.

portfolios. These findings suggest that a significant portion of CSM returns is driven by common movements rather than unidirectional lead-lags between stocks.



(a) Industry momentum (b) BEA customer (c) BEA supplier

(d) Technology link (e) Geographic link (f) Complicated firms

(g) Economic link (h) Analyst coverage

Figure A6. Peer vs focal portfolios: by predictor

This Figure is the same as Panel (a) of Figure 3 but plotted for each individual CSM predictor.

B Controlling for common components

This section provides further details related to controlling common components in cross-stock momentum (CSM).

B.1 Interpreting the symmetric part of CSM

In this section, we explain why the symmetric component of the prediction matrix (Π_{sym}), as defined in Section 3.2, can be interpreted as capturing factor momentum. First, assume realized returns have a factor representation:

$$r_t = Bf_t + \epsilon_t$$

where B is an $N \times K$ loading matrix that remains constant over a short period of time, f_t is the vector of returns of K factors, and ϵ_t is an N-dimensional vector of return residuals. Further, assume that all lead-lag relationships are captured by autocorrelation in factors (e.g., factor momentum):

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

where Λ is a $K \times K$ diagonal matrix, with the diagonal elements representing the factor autocorrelations. Then, it follows that the lagged covariance matrix in stocks is symmetric:

$$Cov(r_{t+1}, r_t') = B\Lambda B'$$

Since CSM predictors are designed to capture the lead-lag relationships in stocks, a CSM predictor that captures factor momentum should also exhibit a symmetric prediction matrix.

B.2 Empirical implementation and comparison of methods

This section describes how we implement the Burt and Hrdlicka (2021) (BH) approach to control for common factors in CSM.

Procedure. For statistical stability, our implementation differs from that of BH, adhering to the methodologies outlined by Fama and French (2020) and common industry practices (e.g., MSCI Barra). Specifically, we directly measure factor loadings from data and factor returns through weighted cross-sectional regressions.

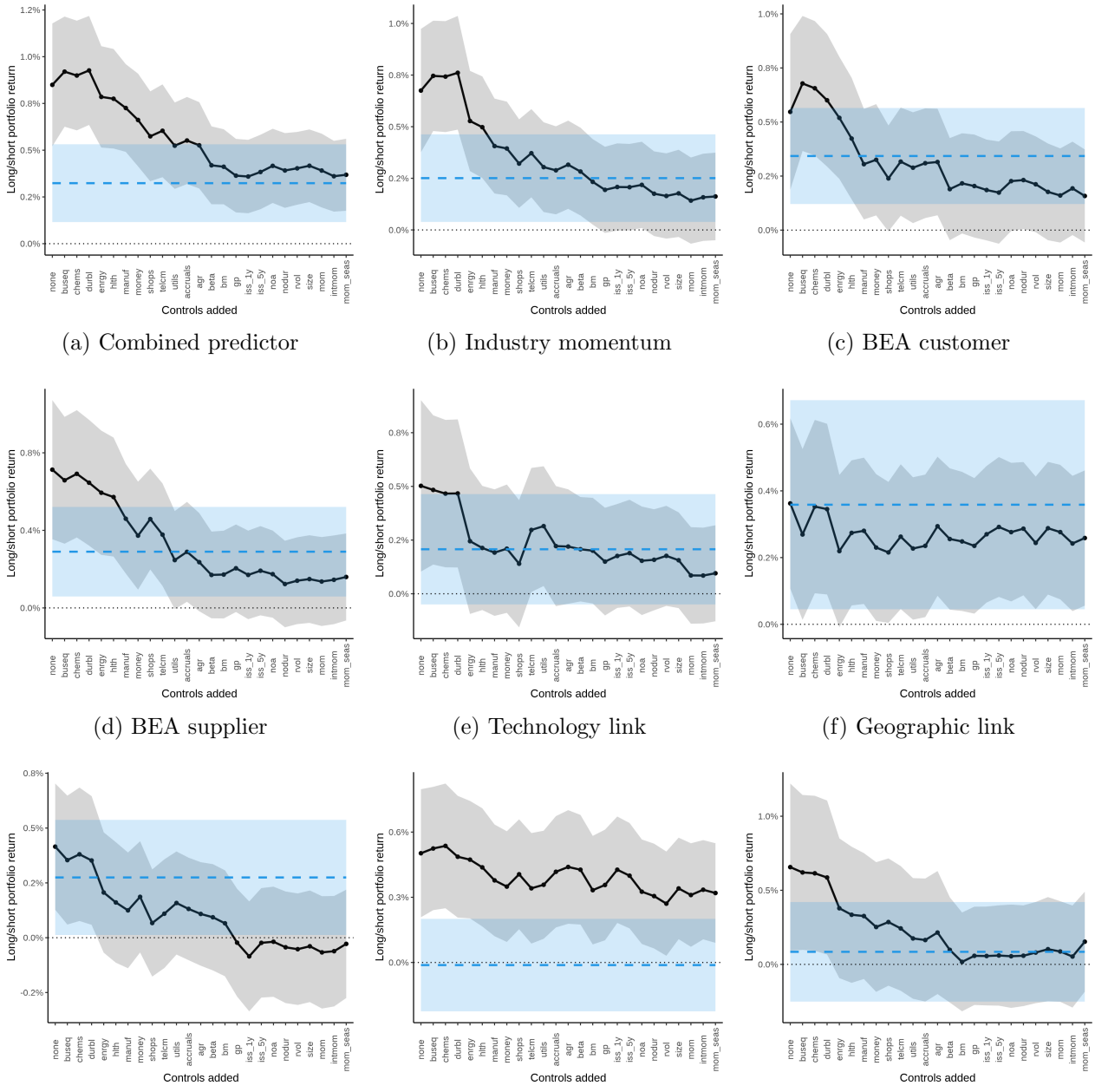
Our implementation begins by controlling for industry dummies and a set of commonly used stock characteristics as loadings $\{b_{i,k}\}_{i,k}$ in Equation (6). For the former, we use dummy variables for the Fama-French 12 industries. For the latter, we download stock characteristics from Chen and Zimmermann (2022), including size, realized volatility, beta, book-to-market, gross profitability, net operating assets, asset growth, 1- and 5-year net issuance, accruals, stock momentum, intermediate momentum, and seasonal momentum. Following Kelly et al. (2019), we transform each characteristic into uniform distributions over -0.5 to 0.5 by rank in each period. Due to the need for characteristics data, we restrict our sample to the period starting from 1963.

In each month t, we estimate a_t and $\{f_{k,t}\}k = 1^K$ in Equation (6) using a cross-sectional weighted least squares regression, where the weight of each stock is the square root of its lagged market capitalization, a method commonly used in the industry (e.g., MSCI Barra). We then use the estimated return residuals $r_{i,t}^{\text{resid}}$ to construct CSM predictors and examine the resulting return predictability on subsequent stock returns (e.g., $r_{i,t+1}$).

Results. To evaluate the impact of controlling for additional factors on the combined CSM predictor, we progressively add the corresponding controls and plot the resulting one-month long-short portfolio return using the black line in Panel (a) of Figure B7. The gray shaded area represents 95% confidence intervals. Without controls, the long-short portfolio generates a monthly return slightly above 1%. As more factors are controlled for, the return steadily decreases and appears to converge towards that of the asymmetric component of CSM, indicated by the blue dashed line with 95% confidence intervals in the blue shaded area.[12] Unreported robustness checks show that the order in which controls are introduced does not significantly affect the results.

The other panels display results for individual CSM predictors. Overall, the results are similar for most predictors, suggesting that the findings based on BH controls converge to ours.

[12]In the figure, we first controlled for all industries before controlling for stock characteristics. Notably, industries have substantial explanatory power over returns, which may seem surprising initially, as industry portfolios are not unconditionally priced. However, they are priced conditionally, explaining their explanatory power over CSM returns.



(a) Combined predictor (b) Industry momentum (c) BEA customer

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

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

Figure B7. Controlling for factors following Burt and Hrdlicka (2021)

We examine the impact of controlling for factor exposures in the construction of CSM predictors on its profitability over the 1963-2017 sample. For each predictor, we progressively add industry and characteristics-based factors, plotting the resulting average monthly return of the long-short NYSE decile portfolio with black lines and 95% confidence intervals in the shaded gray area. The controls added at each step are labeled on the horizontal axis. For comparison, the dashed blue line represents the return of the asymmetric CSM portfolio, with the blue shaded area indicating its 95% confidence interval.