How Much of Cross-Stock Momentum Reflects Underreaction? *

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ABSTRACT

Many studies document cross-stock momentum (CSM) where returns of some stocks predict those of other related stocks, and attribute it to underreaction. We show, however, that CSM returns reverse over time, casting doubt on this interpretation. We decompose CSM into two distinct components. One component is related to the well-known phenomena of factor and stock momentum and accounts for all reversals. The second component captures unidirectional lead–lag effects, does not revert, and its profits mainly derive from liquid stocks leading illiquid ones. We argue that only this second component reflects underreaction and propose a methodology to isolate this effect.

JEL classification: G11, G12, G14

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

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1 Introduction

A substantial 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 stocks predict those of suppliers. Similar return predictability is 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), with overlapping analyst coverage (Ali and Hirshleifer, 2020), and so on. These findings are almost universally interpreted as underreaction to cash-flow information, which may arise from investor inattention or segmentation (e.g., Menzly and Ozbas, 2010).

If underreaction to cash-flow information were the sole mechanism underlying CSM, returns should not revert (Samuelson, 1965). However, our analysis extends existing studies by examining CSM performance over longer holding periods, and we uncover a crucial new finding: CSM returns invariably reverse over time. This reversal pattern directly challenges the notion that underreaction is the sole driver of CSM. To better understand the mechanism, we further show that CSM contains a component that reflects momentum in common factors; this component explains around half of the initial CSM returns and all of the reversals. After removing this common component, the remaining CSM returns are driven by genuinely unidirectional lead–lag relationships, derive returns from liquid stocks leading illiquid ones, and are more consistent with underreaction explanations. Our findings suggest that CSM is a complex phenomenon involving both over- and underreactions, and we recommend that future studies perform similar decompositions to inform interpretation.

We begin by documenting the reversals of CSM returns. We replicate eight prominent CSM predictors and extend their analyses by examining longer-horizon returns after portfolio formation, and find that the initial CSM returns consistently reverse over time. For ease of exposition, we present results primarily for a combined predictor that aggregates across the individual CSM predictors. To visualize the results, we aggregate the eight CSM predictors into a combined one, and form value-weighted, long–short NYSE decile portfolios sorted by this combined CSM predictor. Panel (a) of Figure 1 plots the cumulative post-formation returns of this portfolio. Consistent with prior literature, the portfolio earns high returns within twelve months of formation. However, these returns subsequently reverse. Point estimates from forecasting regressions indicate a full reversal after approximately five years, and the long-term reversal is statistically significant. While we use the combined predictor for presentation, the reversals are present in all individual CSM predictors. The reversal pattern remains robust after excluding stocks below the 20^{th} market capitalization percentile

of NYSE stocks and is not driven by delisting concerns. Price-level-based analysis using the "price wedge" measure of Van Binsbergen et al. (2023) also shows consistent reversals. Taken together, these findings indicate that CSM returns cannot be solely attributed to underreaction to cash-flow news.

[**Figure** 1 about here.]

The finding of return reversals — sometimes interpreted as reflecting overreactions — may be surprising to some readers, given how CSM has traditionally been framed. CSM predictors are constructed to use returns of peer stock A to predict returns of focal stock B. However, a closer examination reveals a disconnect between what the statistical test captures and what researchers intend to measure. The predictive relationship between A and B is not necessarily *unidirectional*. In many cases, returns of stock B also help predict those of stock A, implying the presence of momentum in common components shared across stocks (Burt and Hrdlicka, 2021). Momentum in these common components may be driven by time-varying sentiment or feedback trading — mechanisms that naturally give rise to overreaction and subsequent reversal (Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999). Recognizing this, we hypothesize that the observed return reversals in CSM primarily arise from reversals of common factor returns.

As a preliminary test of this hypothesis, we examine return predictability not only in focal stocks, as in previous studies, but also in peer stocks. Specifically, after CSM portfolio formation, we analyze the subsequent returns of the peer stocks used to construct the CSM predictors. We find that peer stocks exhibit initial momentum and subsequent reversal patterns that closely mirror those of the focal stocks. This finding is consistent with our hypothesis that reversals arise from common components.

As a more formal test, we decompose CSM analytically into a symmetric component and an asymmetric component. This decomposition starts from the observation that all 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 computed as $s_t = \Pi \cdot r_t$, where $\cdot$ is the inner product. To understand this notation, note that for each pair of stocks (i, j), $\Pi_{i,j} > 0$ implies that the CSM predictor uses $r_{j,t}$ to predict $r_{i,t+1}$.

We then split s_t into two additive parts,

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

where Π', which denotes the transpose of Π, captures predictability in the *reverse* direction: if $\Pi_{i,j} > 0$, then $(\Pi')_{j,i} > 0$, which means that $r_{i,t}$ is now used to predict $r_{j,t+1}$. The first decomposed term (s_t^{sym}) in equation (1), which we call the symmetric component of CSM, takes an average between the two directions and thus captures momentum in *common* components. The second term (s_t^{asy}), which we call the asymmetric component, reflects *unidirectional* lead–lags between stocks. We apply this methodology to decompose all eight CSM predictors we study. Consistent with our hypothesis, we find that the symmetric components exhibit strong reversals.

On the positive side, our decomposition methodology appears to identify a genuine component of underreaction within CSM. While the overall CSM returns revert, we show that it is all in the symmetric component; once the symmetric component is removed, the asymmetric component of CSM aligns closely with the underreaction explanation. In addition to not exhibiting reversals, we find that its returns primarily arise from liquid stocks leading illiquid ones, which is consistent with theories of investor inattention and limits to arbitrage. To arrive at this conclusion, we leverage the "prediction matrix" formulation in Equation 1 to further decompose the asymmetric component of CSM into two additive parts: one capturing liquid stocks leading illiquid ones, and the other capturing the opposite direction. When using bid–ask spread and trading volume to proxy for stock liquidity, we find that the profits of asymmetric CSM arise entirely from the first part. This is consistent with the idea that asymmetric CSM reflects information being more quickly incorporated into more liquid stocks.

Pinpointing the precise driver of the symmetric component is challenging, but we show that it is closely related to other forms of momentum. Analytically, symmetric CSM is a generalized version of factor momentum (Gupta and Kelly, 2019; Arnott et al., 2023), which is also related to stock momentum (Ehsani and Linnainmaa, 2022). Consistent with this idea, we find that the symmetric CSM portfolio exhibits return correlations of around 70% with these two other forms of momentum. Moreover, all three exhibit similar twelve-month momentum followed by longer-horizon reversals in the post-portfolio formation period, and symmetric CSM is partially spanned by the other two. In contrast, the asymmetric CSM is

unrelated to factor or stock momentum. While the literature has not reached consensus on the drivers of these reversals, in the context of stock momentum, some researchers attribute them to 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). We do not take a stance on the appropriate interpretation, but we view this as further motivation to control for the symmetric component when isolating the underreaction reflected in CSM returns.

The main contribution of this paper is a nuanced interpretation of CSM. To the best of our knowledge, we are the first to document that CSM returns revert, which casts doubt on the conventional underreaction interpretation. We decompose CSM into the symmetric and asymmetric components, and our findings indicate that only the asymmetric component reflects underreaction. Quantitatively, it accounts for roughly half of CSM returns at the one-month horizon and a minor fraction at the twelve-month horizon. We recommend that future researchers perform similar decompositions to sharpen inference on the magnitude of underreaction.

As a byproduct, we also find that factor momentum reverses — a phenomenon not yet discussed in the factor momentum literature (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023). Taking a historical perspective, our use of long-horizon returns to shed light on CSM aligns with earlier work on stock momentum. In particular, Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) show that stock momentum reverses, lending support to the overreaction interpretation rather than a pure underreaction story.

The rest of the paper is structured as follows. Section 1.1 discusses related literature. Section 2 documents that CSM reverses. Section 3 decomposes CSM and shows that reversals arise from common components. Section 4 provides further tests to analyze each of the decomposed components. Section 5 concludes.

1.1 Related literature

This paper is related to a growing literature that documents cross-stock momentum (CSM) patterns, where returns of related stocks cross-predict each other. These papers propose a variety of ways to measure stock relatedness, including industry classifications (Moskowitz and Grinblatt, 1999), industry input–output matrices (Menzly and Ozbas, 2010), customer–supplier links (Cohen and Frazzini, 2008), technological similarities (Lee et al., 2019), geographic proximity (Parsons et al., 2020), analyst coverage (Ali and Hirshleifer, 2020), labor

links (Liu and Wu, 2022), competition (Eisdorfer et al., 2022), institutional holdings (Ying, 2024), similar stock characteristics (He et al., 2024), news (Scherbina and Schlusche, 2015; Tao et al., 2020; Chen and Wang, 2023; Sak and Chen, 2023; Guo et al., 2025), historical return relationships (Scherbina and Schlusche, 2020; Yan and Yu, 2023), production complementarities (Lee et al., 2024), credit ratings (Feng et al., 2025), and social connections or social media (Peng et al., 2023; Wang and Zhang, 2025). Cohen and Lou (2012) find that the stock returns of conglomerate firms can be predicted by a portfolio of matched standalone firms. Most papers interpret CSM as reflecting underreaction, with the exception of He et al. (2024) and Guo et al. (2025), who argue that their findings represent continued overreaction.

Our paper aims to shed light on the economic interpretation of the CSM phenomenon. Viewed in the context of the broader momentum literature, our approach is related to Lee and Swaminathan (2000) and Jegadeesh and Titman (2001), who also examine the long-horizon returns of stock momentum. Other papers shed light on the interpretation of momentum-style strategies by examining variations in short-horizon returns, including Da et al. (2014), Huang et al. (2021), Huang et al. (2022), Wang (2022), among others.

We find that CSM contains a component that reflects momentum in common factors. This connects our work to the literature on momentum at the portfolio or factor level (Lewellen, 2002; Gupta and Kelly, 2019; Garcia et al., 2021; Ehsani and Linnainmaa, 2022; Arnott et al., 2023; Ehsani and Linnainmaa, 2025). A contemporaneous paper by Favero et al. (2025) also finds that factor returns revert. While corroborative at a high-level, they study dynamically rebalanced factors, while we study long-horizon factor returns with the sorting-period portfolios held fixed. Because we examine returns up to ten years after factor portfolio formation, the portfolios we examine are likely quite different from theirs, especially for factors with fast-moving underlying stock characteristics.

This paper builds on recent advances in understanding CSM, particularly the work of Burt and Hrdlicka (2021) and Yan and Yu (2023). Burt and Hrdlicka (2021) were the first to highlight that CSM returns are partially driven by common factor exposures across related stocks. Our work complements theirs but differs in several respects. First, we have a different core reason — that CSM returns revert over time — for arguing that CSM is not fully driven by underreaction. To our knowledge, this is the first study to document the long-term reversal of CSM returns. Second, using a symmetric–asymmetric decomposition, we further characterize the distinct nature and behavior of these components. We show that the symmetric component is closely related to stock and factor momentum, while the asymmetric component is more consistent with traditional underreaction explanations. Furthermore, we

extend the analysis by examining a much broader set of CSM predictors than previously studied, ensuring our conclusions are robust and generalizable.

2 Cross-Stock Momentum Reverses

This section presents the key finding that cross-stock momentum (CSM) returns reverse. Section 2.1 presents the data and CSM predictors we study. Section 2.2 shows that long-short CSM portfolio returns revert and Section 2.3 presents robustness checks.

2.1 Data and cross-stock momentum predictors

Stocks and characteristics. We obtain monthly prices and returns for US-listed common stocks from the Center for Research in Security Prices (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 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 monthly 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 choose the same list of predictors studied in Yan and Yu (2023). Table 1 summarizes these predictors by the order in which data become available. The one-month look-back version of the industry momentum predictor in Moskowitz and Grinblatt (1999) is available from the beginning of our sample.[1] Following it, the BEA customer- and supplier-based predictors from Menzly and Ozbas (2010) are available from 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 predictor of Ali and Hirshleifer (2020) in 1983. Columns (4) and (5) of the table report the equal- and value-weighted fraction of stocks covered by each predictor after their respective start time. On a value-weighted basis, the industry and analyst coverage predictors encompass over 90% of stocks. The other predictors cover approximately two-thirds of stocks, with the exception of the geographic link predictor which captures slightly less than half of the

[1] We slightly deviate from the original paper's construction by not including the focal stock in constructing the predictor. Specifically, for each focal stock i, its return predictor is the value-weighted average return of all other stocks $j \neq i$ in the same industry.

stock universe. To make CSM predictors more comparable with each other, we follow the literature to transform predictor values into uniform distributions ranging from -0.5 to 0.5 using cross-sectional ranks (e.g., Kelly et al., 2019; Kozak et al., 2020). In unreported tests, we verify that we can closely replicate the main findings of the previous papers.

[**Table** 1 about here.]

A combined CSM predictor. To simplify exposition, much of our analysis starts with a combined predictor that aggregates the eight CSM predictors before presenting results on individual CSM predictors (which are sometimes placed in the Appendix). Following Stambaugh and Yuan (2017), we compute this combined predictor as the average of all available predictor values for each stock-month. For example, between 1953 and 1962, it is computed by averaging values of the three predictors available during that period: industry momentum, BEA-customer, and BEA-supplier predictors.[2] As more predictors become available, the combined predictor incorporates a growing number of inputs.

The advantage of this combination-by-averaging approach lies in its simplicity and transparency. However, a potential concern is that it does not represent an optimal weighting of individual predictors. As a robustness check, 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 procedure. We find that the regression-combined predictor has 95% rank correlation with our simple average-based predictor. Unsurprisingly, all our results remain robust to this alternative method.

2.2 Cross-stock momentum reverses

As discussed in Section 1, if the CSM returns are entirely due to underreaction to cash flow news, these returns should not revert (Samuelson, 1965). This implication has not been rigorously tested in the prior literature, possibly reflecting researchers' conviction that reversals are unlikely.

[**Figure** 2 about here.]

To test whether reversals occur, we follow Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) to trace the cumulative returns after portfolio formation. Specifically, in each

[2]When a predictor becomes available but has missing values for certain stocks, we fill in zeros for them, which correspond to cross-sectional medians, because the predictors are transformed to uniform distributions from -0.5 to 0.5.

portfolio formation month (or "vintage") t, we sort stocks into NYSE deciles using a CSM predictor with values $s_{i,t}$. 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 market capitalization in month $t+h-1$, and $r_{i,t+h}$ is the return of stock i in month $t+h$. Then, for each vintage t, the one-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 the combined CSM predictor which is defined in Section 2.1, 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 by a bootstrap procedure described in Appendix A.2. Consistent with the previous literature, we observe positive returns within one year of portfolio formation. However, we find that these returns reverse subsequently, with the point estimate indicating full reversal after approximately five years.

[**Table** 2 about here.]

The reversal is not specific to the combined predictor but is present in all individual CSM predictors. Figure 2 plots the cumulative post-formation portfolio returns for each individual predictor. Although there is variation in timing and magnitude of the reversals, the point estimates indicate full reversal of the initial CSM returns after five to ten years for all predictors.

The return reversal is statistically significant for the combined CSM predictor and for most individual predictors. Table 2 reports average cumulative returns over various event windows following portfolio formation. Each column labeled $m \to n$ shows the cumulative return from month $t+m$ (inclusive) to $t+n$ where t is the portfolio formation month. Columns (1) and (2) indicate that all CSM-sorted long–short portfolios generate positive returns over the 1- and 12-month horizons, consistent with prior literature. To analyze reversals, columns (3) through (5) present cumulative returns over 5-, 7-, and 10-year horizons after skipping the first year. At the 5-year horizon, the combined predictor shows a return reversal of -1.54%, which is statistically significant at the 10% level. The reversal strengthens to -2.20% and -4.65%, becoming statistically significant at the 5% and 1% levels, respectively, at the 7- and 10-year horizons. Among the individual CSM predictors, all exhibit negative cumulative

returns by the 10-year mark, with five out of eight reversals statistically significant at the 5% level.

It is well known that detecting long-horizon return reversals is challenging when using slow-moving return predictors, and the reader may wonder why we obtain statistically significant results. The key difference lies in the nature of our predictor: it is *fast-moving*. Recall that CSM predictors are constructed using one-month returns. That is, portfolios formed at times t and $t+1$ are based on returns from months t and $t+1$, respectively. Because returns exhibit limited autocorrelation, these portfolios differ substantially over time. As a result, when we compute average long-horizon returns of the form $\frac{1}{T}\sum_{t=1}^{T} \text{cumret}_{t+m\to t+n|t}$, we are effectively averaging over approximately T independent observations. This contrasts with slow-moving predictors like firm size, where portfolios sorted in months t and $t+1$ are nearly identical, reducing the effective number of independent observations. The fast-moving nature of CSM thus provides greater statistical power to detect return reversals. Previous studies on CSM have not examined post-portfolio-formation returns over long horizons. Among the papers we replicate, the longest horizon considered is Parsons et al. (2020), who analyze returns up to 24 months.[3] Most other papers focus on shorter horizons and therefore have not identified the long-term reversal. While Burt and Hrdlicka (2021) do examine long-horizon returns, they study "same-month returns"—that is, whether returns in January predict returns in Januaries of subsequent years. They find that same-month returns exhibit long-horizon continuation, which they attribute to seasonality effects (Heston and Sadka, 2008; Keloharju et al., 2016). In contrast, we examine post-portfolio-formation returns across all months and find that reversal effects dominate.

Our findings have implications for the economic interpretation of CSM returns. Given the observed reversal, it is difficult to interpret all CSM returns as underreaction, as is often assumed in the literature. In the language of the behavioral literature (e.g., Daniel et al., 1998), this suggests that CSM must contain a component representing "overreaction," where prices deviate further before converging back toward long-run equilibrium.[4]

[3] Although they employ a different methodology, the results in their Figure 4 are qualitatively consistent with ours, as their point estimates also suggest that reversal begins after approximately 12 months.

[4] Using a different methodology and terminology, Van Binsbergen et al. (2023) show that most cross-sectional anomalies and predictors reflect underreaction — referred to as "resolution anomalies" in their paper. Only a small subset of anomalies — notably momentum and profitability — reflect overreaction, or "build-up" anomalies.

2.3 Robustness

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

Alternative delisting treatments. When a firm delists in month $t+h$, we assume it earns the delisting return in that month, and the remaining dollar value is reinvested into the other stocks starting in month $t+h+1$. For delisting returns, we use the values reported in CRSP when available. If unavailable, we follow the literature and assign -55% for NASDAQ stocks and -30% for others (Shumway, 1997; Shumway and Warther, 1999).

Appendix A.1 shows that the return reversal is robust to alternative delisting treatments, including the methodology of Hou et al. (2020). We also find that the fraction of stocks that delist is similar between the long and short legs of CSM portfolios, suggesting our results are not driven by delistings. Specifically, on a value-weighted (equal-weighted) basis, 84.5% and 86.7% (71.8% and 73.1%) of stocks in the long and short portfolios, respectively, survive after 10 years.

Price-level analysis. Instead of examining long-horizon cumulative *returns*, a complementary approach is to study deviations in price *levels*, as proposed by Van Binsbergen et al. (2023) and 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 "price wedge" measure, which captures the extent to which price levels deviate from long-run equilibrium. Results from their approach align with ours: CSM-sorted long–short portfolios see an initial increase in the price wedge within twelve months of formation, followed by a gradual reversal, consistent with our finding of long-run return reversals.

Alternative portfolio constructions. In Appendix A.3, we show that our finding of return reversal is robust to alternative portfolio constructions, including equal-weighted portfolios and long–short quintile (instead of decile) portfolios.

3 Decomposing Cross-Stock Momentum

In this section, we decompose cross-stock momentum (CSM) into components to better understand why it reverses. Although CSM findings are often framed as *unidirectional* lead–lag relationships (e.g., peer stocks leading focal stocks), such apparent relationships can also arise from momentum in common components. Specifically, peer and focal stocks

may load on common factors that themselves exhibit momentum. Following this reasoning, Section 3.1 first demonstrates that a significant portion of CSM reflects common movements between peer and focal stocks. Section 3.2 then proposes a method to separate the common components, and Section 3.3 shows that they account for the entire reversal.

3.1 Common components revert: preliminary evidence

To preliminarily examine the common components of CSM predictors, we analyze the peer portfolios alongside the focal portfolios. Recall that for a given CSM predictor, each focal stock i is linked to a peer portfolio through weights $\{\Pi_{i,j}\}_{j=1}^{N}$. Given a focal portfolio with weights $\{w_i^{\text{focal}}\}_{i=1}^{N}$, we also construct a corresponding peer portfolio by applying the same focal weights to the peer connections.[5] The existing literature typically focuses on the focal portfolios. To examine possible common components shared by focal and peer stocks, however, we also analyze the behavior of the peer portfolios.

[**Figure** 3 about here.]

Figure 3 plots the cumulative returns of the long–short peer portfolios alongside the focal portfolios for the combined CSM predictor. We observe strikingly similar momentum and reversal patterns, suggesting that these dynamics are driven by common components shared between focal and peer stocks. While the figure shows results only for the combined CSM predictor, Appendix A.6 reports broadly similar findings for each individual CSM predictor. Overall, the results strongly suggest that a common component accounts for the reversals in CSM.

3.2 CSM Decomposition

Motivated by the findings in Section 3.1, we seek to separate CSM into the common components and the rest. To do so, we adapt the approach of Yan and Yu (2023) and decompose CSM into "symmetric" and "asymmetric" components. The symmetric component captures common factor movements,[6] while the asymmetric component reflects unidirectional lead–lag relationships — arguably more aligned with the original motivation behind CSM research.

We now describe the decomposition methodology and provide intuition for how to interpret these two components. We start by noting that all CSM predictors can be expressed in the

[5] Specifically, the weight on each stock j in the peer portfolio is given by $\frac{\sum_{i=1}^{N} w_i^{\text{focal}} \cdot \Pi_{i,j}}{\sum_{i=1}^{N} w_i^{\text{focal}}}$.

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

following general form:

$$s_t = \Pi_t \cdot r_t \tag{4}$$

where s_t is an N-dimensional vector of return predictor values, Π_t is an $N \times N$ "prediction matrix," and r_t is the vector of stock returns in month t. CSM effects correspond to using s_t to predict r_{t+1}. Because the prediction matrices we examine tend to be slow-moving with half-lives at least around five years (Figure 4 in Yan and Yu (2023)), we write Π instead of Π_t to economize on notation.

Note that the rows of Π correspond to the peer portfolio weights for each focal stock.[7] Appendix B.1 provides detailed examples of how different CSM predictors can be represented using Equation (4).

Given this formulation, both the prediction matrix and the predictors can be additively decomposed into symmetric and asymmetric components:

$$\Pi = \underbrace{\left(\frac{\Pi + \Pi'}{2}\right)}_{\equiv \Pi_{\text{sym}}} + \underbrace{\left(\frac{\Pi - \Pi'}{2}\right)}_{\equiv \Pi_{\text{asy}}} \tag{5}$$

$$s_t = \underbrace{\Pi_{\text{sym}} \cdot r_t}_{\equiv s_t^{\text{sym}}} + \underbrace{\Pi_{\text{asy}} \cdot r_t}_{\equiv s_t^{\text{asy}}}. \tag{6}$$

We now provide simplified examples to give intuition about what each component captures.

A symmetric case. Consider a CSM predictor specified as:

$$\underbrace{E_t \begin{bmatrix} s_{1,t} \\ s_{2,t} \end{bmatrix}}_{=s_t} = \underbrace{\begin{bmatrix} 0.1 & 0.1 \\ 0.1 & 0.1 \end{bmatrix}}_{=\Pi} \cdot \underbrace{\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix}}_{=r_t}$$

where s_t captures the researcher's prediction of $E_t(r_{t+1})$. This predictor clearly contains no unidirectional lead–lag effects. Instead, the return predictability is fully driven by momentum

[7] For example, 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:

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

Here, $M_{k,t}$ denotes the market capitalization of stock k, and $\text{ind}(k)$ is the industry it belongs to.

in a common component shared by the two stocks. Consistent with this intuition, the entire prediction matrix is captured by the symmetric part:[8]

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

A case with unidirectional lead–lags. Now consider a slightly modified prediction matrix:

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

This predictor contains both a common component and a unidirectional lead–lag component. Specifically, $r_{2,t}$ helps forecast $r_{1,t+1}$, but $r_{1,t}$ does not help forecast $r_{2,t+1}$. This directional influence — stock 2 leading stock 1 — is captured by the asymmetric component:

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

where, as expected, Π_{asy} reflects a unidirectional lead–lag from stock 2 to stock 1. To better understand the origins of asymmetric components in practice, Appendix B.1 further discusses this using specific CSM predictors in the literature as examples.

3.3 The common component accounts for the reversal

We now decompose each CSM predictor into symmetric and asymmetric components. Specifically, for each predictor $k = 1, \ldots, 8$, we decompose the predictor values as $s_{i,t}^k = s_{i,t}^{k,\text{sym}} + s_{i,t}^{k,\text{asy}}$.[9] For normalization, we convert each symmetric and asymmetric CSM predictor into a

[8] To further understand the common component, note that a principal component analysis of Π_{sym} yields:

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

indicating that the predictability is entirely driven by momentum in the portfolio with equal weights on stocks 1 and 2 (corresponding to the first principal component).

[9] By construction, each row of Π sums to one, implying that the predictive portfolio for each stock i has a leverage of one. In contrast, the rows of Π_{sym} and Π_{asy} generally do not sum to one. To ensure that the symmetric and asymmetric predictors are comparable to the original CSM predictor in this regard, we re-normalize each row of Π_{sym} and Π_{asy} so that the sum of their absolute weights equals one. However, our results are not materially affected without this renormalization.

uniform distribution over $[-0.5, 0.5]$ based on their cross-sectional ranks. For the combined predictor, we construct its symmetric and asymmetric components following the procedure described in Section 2.1, by averaging the corresponding components of the available individual predictors; that is, $s_{i,t}^{\text{combined, sym}} = \frac{1}{K}\sum_{k=1}^{K} s_{i,t}^{k,\text{sym}}$, and similarly for the asymmetric component. We then form long–short portfolios separately using the symmetric and asymmetric predictors.[10]

To assess the contribution of these two components, Panel (b) of Figure 1 plots the cumulative returns of the symmetric and asymmetric components of the combined CSM predictor. The symmetric component accounts for most of the initial 12-month return and all of the subsequent reversal. In contrast, the asymmetric component shows no evidence of reversal. Appendix Figure B2 reports broadly similar patterns for the individual CSM predictors.

To facilitate a more detailed comparison between the two components, we report their average portfolio returns in Table 3. We find that the symmetric component accounts for most of the short-horizon returns and all of the long-horizon reversals. Specifically, the first four rows examine the full sample. The first row reproduces the results from Table 2 for the long–short portfolio formed using the original combined CSM predictor ("total"). The next two rows report results for portfolios formed using the symmetric and asymmetric predictors, respectively, and show that most of the return variation is explained by the symmetric component. Importantly, reversals occur only in the symmetric component. In contrast, the asymmetric component exhibits statistically significant positive returns in the first month and no reversals.[11] The fourth row reports, for the 1- and 12-month horizons, the ratio of asymmetric to total long–short portfolio returns. The results indicate that approximately 47% (10%) of 1-month (12-month) CSM returns are attributable to the asymmetric component.

The remainder of the table examines two subsamples, splitting the full sample into pre- and post-1963 periods. The first subsample runs through 1962 and includes the industry momentum, BEA customer, and BEA supplier predictors. The second subsample starts in 1963, a common start date in asset pricing studies due to greater availability of stock characteristics. The conclusions are qualitatively consistent across subsamples: the symmetric component accounts for the full reversal, while the asymmetric component explains a subset of short-horizon returns.

[10] Appendix A.6 shows that removing the symmetric components effectively eliminates the covariance between focal and peer portfolios, consistent with the idea that the symmetric component captures common comovements.

[11] While we define the symmetric and asymmetric predictors to sum to the original CSM predictor at the *stock level*, the long–short returns formed from these predictors do not necessarily sum to the returns of the original predictor.

[**Table** 3 about here.]

We then examine the fraction of returns attributable to the asymmetric component for individual CSM predictors. Detailed results are reported in Appendix B.2; here we summarize the key findings visually. Figure 4 plots the one-month portfolio results by predictor. Panel (a) shows portfolio returns for the original (asymmetric) CSM predictors in blue (red), with whiskers indicating 95% confidence intervals. For all predictors, the point estimate of the asymmetric component is smaller than that of the original CSM predictor. Panel (b) shows the ratio of asymmetric to total returns, with whiskers indicating 95% confidence intervals. For four of the eight predictors, we reject the null hypothesis that the asymmetric component is as strong as the full CSM component at the 5% level. Overall, the results are broadly consistent with the idea that only a subset — on average about half — of CSM returns can be attributed to the asymmetric component.

[**Figure** 4 about here.]

4 Interpreting Decomposed CSM Components

Our main finding — that CSM returns revert — suggests that the underreaction explanation does not fully account for the observed patterns. However, the symmetric–asymmetric decomposition provides a more nuanced perspective, indicating that the reversal is entirely concentrated in the symmetric component. This suggests that, by controlling for the symmetric component and focusing on the asymmetric component, we may isolate the portion of CSM that genuinely reflects underreaction. The results presented in this section are consistent with this interpretation. Section 4.1 argues that the asymmetric component is closely aligned with the traditional underreaction hypothesis. Section 4.2 shows that the symmetric component is related to factor and stock momentum. Based on these findings, we suggest that researchers interested in underreaction should primarily focus on the asymmetric component.

4.1 The asymmetric component: liquid stocks lead illiquid ones

The results so far suggest that the asymmetric component may represent underreaction. By construction, the asymmetric component captures unidirectional lead-lag relationships that align more closely with the notion of underreaction — where some stocks respond to information more quickly than others, and thereby act as leaders. As shown in Section 2.2, this component does not revert, which is also consistent with the underreaction interpretation.

In this section, we provide further evidence that the return predictability in the asymmetric component of CSM is primarily driven by liquid stocks leading illiquid ones, but not in the reverse direction.

We examine how returns differ based on stock liquidity because theory predicts a relationship between stock liquidity and the speed of information incorporation, via two mechanisms. First, when investors face limited capacity for processing or acquiring information, they would find it more advantageous to allocate more attention to liquid stocks, where a given informational advantage yields greater potential profits (Van Nieuwerburgh and Veldkamp, 2010). Second, arbitrageurs can more readily trade on mispricings in liquid stocks, accelerating the adjustment of prices to information. Both mechanisms suggest that if the asymmetric component captures underreaction, a substantial portion of return predictability should originate from liquid stocks leading illiquid ones.

To test this prediction, we proxy for stock liquidity using lagged bid-ask spreads and dollar trading volume. For the bid-ask spread, we use the estimator of Corwin and Schultz (2012), which is based on daily high and low prices and allows us to extend the sample back to the beginning of the CRSP dataset. Dollar trading volume is computed as share volume multiplied by end-of-month price, both sourced from CRSP's monthly files. To reduce measurement noise, both liquidity measures are smoothed using an exponentially weighted average over the past twelve months $(t-12,\ldots,t-1)$, with weights calibrated via predictive regressions.[12] To examine variation across the full spectrum of stock liquidity, we include stocks below the 20% NYSE size cutoff, which had previously been excluded.

Double-sort results. In each month, we sort stocks into terciles based on liquidity proxies. We then examine $3 \times 3 = 9$ portfolios corresponding to combinations where peer stocks are drawn from one liquidity tercile and focal stocks from another. [13] As before, we form value-weighted long-short NYSE decile portfolios and compute their monthly returns. Results for the combined CSM predictor are reported in Table 4. The first four columns use lagged bid-ask spreads to proxy for liquidity. To interpret the table, observe that the first row of column (3) corresponds to the case where high-liquidity peer stocks are used to predict

[12] Specifically, for each liquidity measure x, we estimate a panel regression of $x_{i,t}$ on its twelve monthly lags, then fit an exponential decay curve to the twelve estimated coefficients. The resulting decay implies a half-life of approximately one month. We use the fitted coefficients to compute the predicted value of $x_{i,t}$.

[13] Specifically, for each pair of liquidity terciles $j,k \in \{1,2,3\}$, we use stocks in the j^{th} tercile as peer stocks to predict returns of those in the k^{th} tercile as focal stocks. To implement such portfolios, we begin with the asymmetric prediction matrix Π_{asy} and extract a submatrix containing only the rows and columns corresponding to stocks in terciles j and k, respectively. We then compute predictors and form portfolios using this submatrix.

returns of low-liquidity focal stocks; the resulting monthly return is 1.13%, with a standard error of 0.21%.

[**Table** 4 about here.]

We observe two main findings. First, when comparing across rows, we find stronger return predictability when focal firms are illiquid. The last row of the table shows that, controlling for peer stock liquidity, focal stocks with lower liquidity exhibit higher return predictability, and the difference is statistically significant except for the case when peer stocks are also of the lowest liquidity tercile.

Second, when comparing across columns, we see that return predictability primarily arises from peer stocks with high liquidity acting as leaders. Column (4) reports the difference in return predictability when controlling for focal firm liquidity and varying peer firm liquidity. These differences are statistically significant at the 1% level and economically meaningful. Using high-liquidity peer firms to predict low-liquidity focal firms yields returns over 1% per month. In contrast, using low-liquidity peer firms to predict others does not produce statistically or economically significant results.

The second finding is particularly informative for understanding the underlying mechanism. The first result — that return predictability is strongest in illiquid focal firms — is also commonly found in most return predictors (e.g., Hou et al., 2020). The second result is novel and specific to CSM. Overall, these findings support the idea that a significant portion of asymmetric CSM returns arises from liquid stocks leading illiquid ones.

Decomposition by peer–focal stock pairs. To quantify the *fraction* of the asymmetric CSM return attributable to liquid stocks leading illiquid ones, we further decompose returns in a more granular way at the level of peer–focal stock pairs. We find that nearly all of the asymmetric CSM return arises from liquid stocks leading illiquid ones, with essentially no return predictability in the reverse direction.

To enable this decomposition, we modify the long–short decile CSM portfolio construction to directly use the predictor values $s_t^{\text{asy}} = \Pi_{\text{asy}} \cdot r_t$ as portfolio weights, so that the portfolio return in month $t+1$ is $r_{t+1}' s_t^{\text{asy}} = r_{t+1}' \Pi_{\text{asy}} r_t$. This portfolio construction is similar to that in Kozak et al. (2020) and Kelly et al. (2023). We adjust the leverage of the portfolio to achieve a gross exposure of 200%, matching the earlier long–short portfolio which has 100% gross exposure on both the long and short sides.[14] In each month, we sort stocks by liquidity

[14] That is, we use as portfolio weights $\tilde{s}_t^{\text{asy}} = \frac{2}{\iota_N' |s_t^{\text{asy}}|} s_t^{\text{asy}}$, where ι_N is a vector of ones.

proxies such that stocks 1 and N are the most and the least liquid, respectively. Then, for any asymmetric CSM portfolio, its return can be decomposed into three parts,

$$\sum_{i,j=1}^{N} r_{i,t+1}\Pi_{\text{asy},i,j}r_{j,t} = \underbrace{\sum_{j<i} r_{i,t+1}\Pi_{\text{asy},i,j}r_{j,t}}_{\text{liquid} \to \text{illiquid}} + \underbrace{\sum_{j>i} r_{i,t+1}\Pi_{\text{asy},i,j}r_{j,t}}_{\text{illiquid} \to \text{liquid}} + \underbrace{\sum_{j=i} r_{i,t+1}\Pi_{\text{asy},i,j}r_{j,t}}_{\text{self effect} = 0}, \tag{7}$$

where the first term captures profits from liquid stocks leading illiquid stocks and the second captures the reverse direction. The third term is identically zero because all diagonal elements of Π_{asy} are zero by construction. [15]

We present the decomposition results in Table 5. In the first three columns, stock liquidity is proxied by the bid–ask spread. In the first row, which examines the asymmetric component of the combined CSM predictor, we find a monthly return of 2.01%, entirely arising from liquid stocks leading illiquid ones (2.11%). In contrast, using illiquid stocks to predict liquid ones generates a return that is approximately zero and statistically insignificant. The subsequent rows study individual CSM predictors and find broadly similar patterns: most of the return predictability arises from liquid stocks leading illiquid ones. It is worth noting that the number of stock pairs used to construct the two components is the same. If stock liquidity were unrelated to return predictability, we would expect the two components to generate similar returns, but the results clearly indicate that returns predominantly arise from liquid stocks leading illiquid ones. In the last three columns, we use trading volume to proxy for stock liquidity and find broadly similar results.[16]

[**Table** 5 about here.]

Overall, the results in this section indicate that the asymmetric component of CSM profits arises from liquid stocks leading illiquid ones. This is consistent with the idea that the asymmetric component reflects underreaction to information.

[15] Methodologically, this decomposition exercise is conceptually similar to the work of Lo and MacKinlay (1990) and Yan and Yu (2023)

[16] The value differences between columns (1) and (4) are due to sample differences arising from the availability of liquidity proxies. The asymmetric component of the Complicated firms predictor shows a negative return here, and the difference from earlier results based on long-short deciles is due to the different portfolio construction.

4.2 The symmetric component: relationship with factor and stock momentum

In our decomposition of CSM into symmetric and asymmetric components, our primary interest lies in the latter. We argue that it reflects underreaction to information, which is the core interest of CSM research. From this perspective, we view the symmetric component as a confounding effect to be controlled for. For completeness, however, we also examine the symmetric component in this section. We show that it is related to both factor momentum (FM, Gupta and Kelly, 2019; Arnott et al., 2023) and stock momentum (MOM, Jegadeesh and Titman, 1993). All three forms of momentum exhibit similar 12-month return continuation followed by reversals.

Why may the symmetric CSM be related to other forms of momentum? The analytical structure of the symmetric component of CSM lends itself to being understood as a generalized version of factor momentum. Consider the symmetric component of the prediction matrix $\Pi_{\text{sym}} = \frac{\Pi+\Pi'}{2}$. Perform a principal component decomposition:

$$\Pi_{\text{sym}} = W \cdot \Lambda \cdot W'$$

where Λ is a diagonal matrix and W is an $N \times N$ orthonormal matrix. We can rotate stock returns into the space of orthogonal factors defined as $f_t = W' r_t$, and the diagonal elements of Λ capture the autocorrelation of these factors. This suggests that the symmetric CSM can be viewed as a generalized form of the factor momentum studied by Gupta and Kelly (2019) and Arnott et al. (2023). In the factor momentum literature, researchers examine return predictability in a similar format, but with two key differences: they use pre-specified factor portfolios W and assume that the diagonal elements of Λ are equal.

Ehsani and Linnainmaa (2022) further argue that stock momentum is closely related to factor momentum. Taken together, these insights lead us to hypothesize that the symmetric component of CSM is related to both stock momentum and factor momentum. If such a connection exists, then the reversal in CSM may correspond to the reversals in stock momentum documented by Lee and Swaminathan (2000) and Jegadeesh and Titman (2001); we would also expect factor momentum to exhibit similar reversals.

Constructing other momentum portfolios. We construct a simplified version of FM following the "cross-sectional factor momentum" methodology of Arnott et al. (2023). They start with a set of characteristics-based long–short factors and construct the FM strategy

by going long (short) in the top (bottom) half of factors based on their most recent month's performance. They argue that the exact set of factors chosen is not critical for their results.

Following their methodology, we construct a simplified version of their strategy. Our version is built upon thirteen characteristics-sorted value-weighted long–short NYSE decile 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. While Arnott et al. (2023) focus on one-month post-portfolio-formation performance, we extend the horizon to examine FM's long-run returns after portfolio formation, mirroring our approach with CSM.[17]

To capture the stock momentum effects documented by Jegadeesh and Titman (1993), we also construct a value-weighted long–short portfolio that goes long the top and short the bottom NYSE decile of stocks sorted on the previous month's returns (Jegadeesh, 1990). We refer to this portfolio as MOM and also examine its long-run post-portfolio-formation returns.[18]

We use the sample starting in 1963 to study the relationship between CSM, FM, and MOM,

[17] In each portfolio formation month t and for each factor $k = 1, \ldots, K$, we first sort stocks by the corresponding characteristic into deciles $D^k_{1,t}, \ldots, D^k_{10,t}$. We obtain the portfolio 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 halves 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 by Arnott et al. (2023). Our innovation is to also examine longer horizons $h > 1$.

[18] The classical stock momentum predictor uses returns from the previous 12 months (excluding the most recent month) to predict the next month's return, effectively capturing covariances of the form $\{\text{Cov}(r_{t-l}, r_t)\}^{12}_{l=2}$. As a comparison, our predictor uses the most recent month's return to forecast future returns, which matches the timing of CSM construction to enable a direct comparison. When examining forecasting horizons up to one year, it captures covariances of the form $\{\text{Cov}(r_t, r_{t+h})\}^{12}_{h=1}$, which are equivalent to those captured by the classical momentum predictor if returns are stationary.

as most stock characteristics needed to construct FM become available beginning in 1963.

Relationship between CSM and the other momentum portfolios. We first observe that CSM, FM, and MOM — each constructed by sorting stocks based on some version of one-month returns — are highly correlated. Panel (a) of Figure 5 shows the monthly return correlations of the various momentum portfolios, including the symmetric and asymmetric components of CSM. We observe that CSM has return correlations of 0.68 and 0.71, respectively, with FM and MOM. This correlation arises entirely from the symmetric component, while the asymmetric component has very little relationship with the other forms of momentum.

After examining the covariance of returns, we then examine average return patterns after portfolio formation in Panel (b). We find that all three forms of momentum exhibit strikingly similar patterns of return continuation within 12 months of portfolio formation, followed by subsequent reversals.[19]

[**Figure** 5 about here.]

Spanning tests We now assess the extent to which FM and MOM explain CSM using spanning regressions. We estimate regressions of the form:

$$\text{CSM}_{t+m\to t+n|t} = a + b_{\text{FM}} \cdot \text{FM}_{t+m\to t+n|t} + b_{\text{MOM}} \cdot \text{MOM}_{t+m\to t+n|t} + \epsilon_{t+m\to t+n|t}$$

where $X_{t+m\to t+n|t}$ represents the cumulative return from month m (inclusive) to month n for the X portfolio formed in month t.

We start with the one-month horizon ($m = n = 1$). Because MOM exhibits one-month reversals, it cannot possibly span CSM, so we only include FM as the independent variable. Results are reported in Table 6. Over the post-1963 sample, the CSM portfolio has monthly return of 0.87%, which declines to approximately half when controlling for FM. CSM has a significant loading of 0.73 on FM. After decomposition, we see that the loading and explanatory power by FM arise from the symmetric component. The asymmetric component has no statistically significant relationship with FM.

[**Table** 6 about here.]

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

We then examine longer horizons in Table 7. Panel A reports horizons of 2 to 12 months after portfolio formation. CSM exhibits 2.08% return at this horizon and it is entirely due to the symmetric component. We find that it has sizeable loadings on both FM and MOM, and controlling for these two variables can fully explain away the returns. Panel B examines the return reversals beyond the first year and finds that controlling for FM and MOM can explain approximately half of the reversals.

[**Table** 7 about here.]

Overall, these analyses lead us to conclude that the symmetric component of CSM is closely related to the known effects of MOM and FM. Therefore, the reversal in CSM is at least partially tied to the well-documented pattern of stock momentum reversals (Lee and Swaminathan, 2000; Jegadeesh and Titman, 2001). While there is no consensus on exactly what drives the reversal, some researchers argue that it reflects an "overreaction" phenomenon, possibly arising from sentiment or positive-feedback trading (Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999). This supports our argument that the symmetric component cannot be interpreted as underreaction and should be controlled for in studying CSM.

As a by-product, our analysis reveals that factor momentum exhibits reversals — a finding that has not yet been emphasized in the factor momentum literature. A contemporaneous paper, Favero et al. (2025), also documents that returns of factor portfolios revert over time. As such, their results also indicate that factor momentum reverses. The main difference is that they examine factors that are continuously rebalanced, whereas we study long-run returns of factors without rebalancing — a difference that is more pronounced for factors based on characteristics that change more quickly. That said, we view their results as complementary and corroborative.

5 Conclusion

Over several decades, researchers have documented many instances of cross-stock momentum (CSM) patterns, where returns of peer stocks predict those 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.

To explain these reversals, we note that a substantial portion of CSM does not reflect uni-

directional lead–lag relationships — which are arguably the main focus of CSM research — but instead arises from momentum in common factors. We use an analytical identity to decompose CSM into two parts: a symmetric component that captures momentum in common factors, and an asymmetric component that reflects unidirectional lead–lag relationships. Our analysis shows that the symmetric component contributes to the initial momentum while fully explaining the subsequent reversals. This common component is closely related to factor and stock momentum, and its behavior is inconsistent with underreaction.

We argue that the remaining asymmetric component — which accounts for roughly half of the one-month and a smaller fraction of the one-year post-formation CSM returns — aligns with the traditional underreaction explanation. Asymmetric CSM returns do not revert and predominantly arise from liquid stocks predicting illiquid ones, but not vice versa. Overall, we offer a more nuanced interpretation of CSM returns. We recommend that future research remove the symmetric component when assessing the economic magnitude of underreaction in CSM returns, and conduct additional tests on the underlying mechanism to further clarify its economic interpretation.

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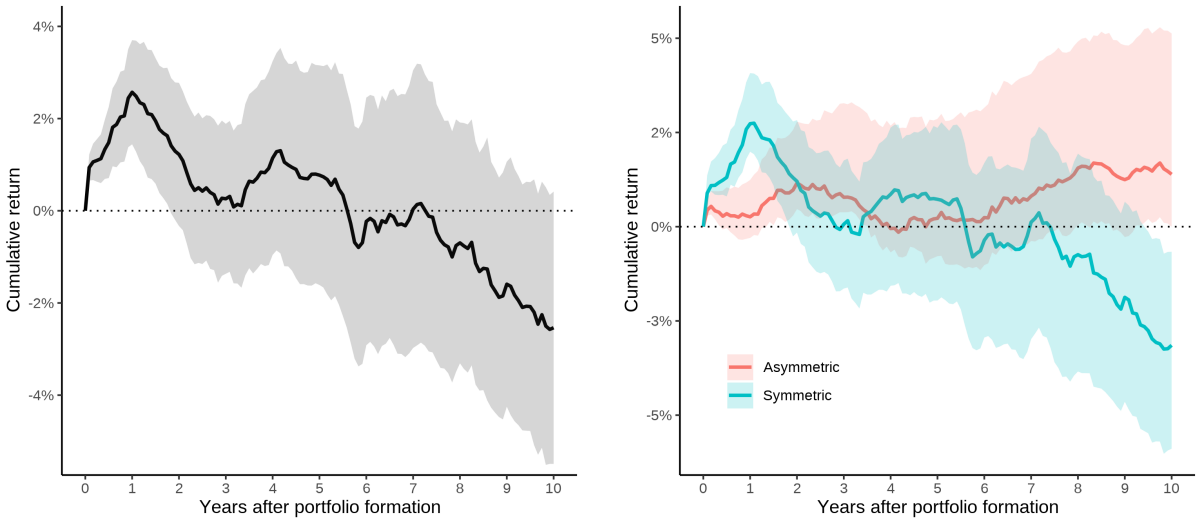
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(a) Cross-stock momentum

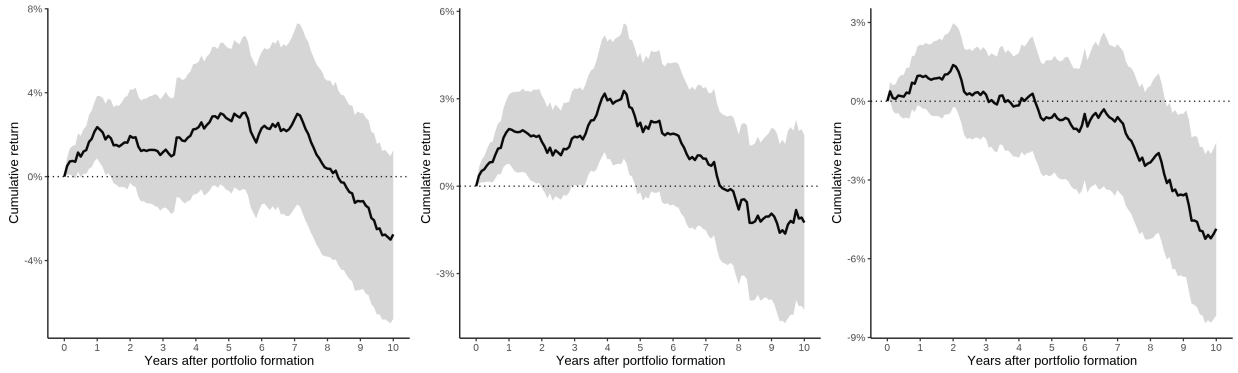
(b) Decomposed cross-stock momentum

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

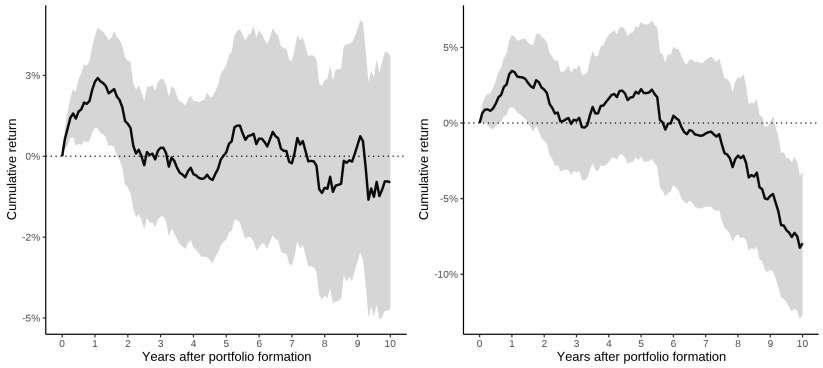
We analyze the cumulative returns of long–short, value-weighted NYSE decile cross-stock momentum (CSM) portfolios. The sorting variable, detailed in Section 2.1, aggregates eight CSM predictors from the existing literature. Panel (a) shows cumulative returns up to ten years after portfolio formation. Panel (b) further decomposes the CSM 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 methodology is explained in Section 3. In both panels, shaded areas represent 95% bootstrapped confidence intervals.



(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 returns of long-short value-weighted NYSE decile portfolios formed by sorting on individual CSM predictors. The shaded areas represent 95% bootstrapped confidence intervals. The predictors are ordered by the time at which they become available.

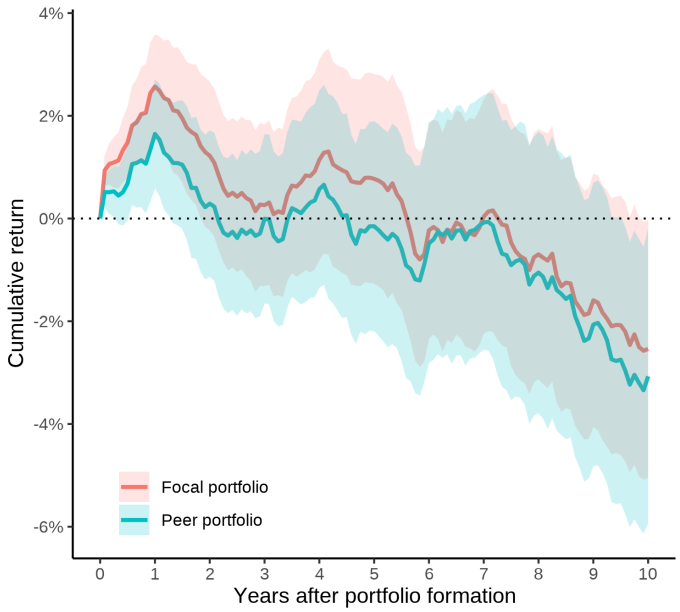
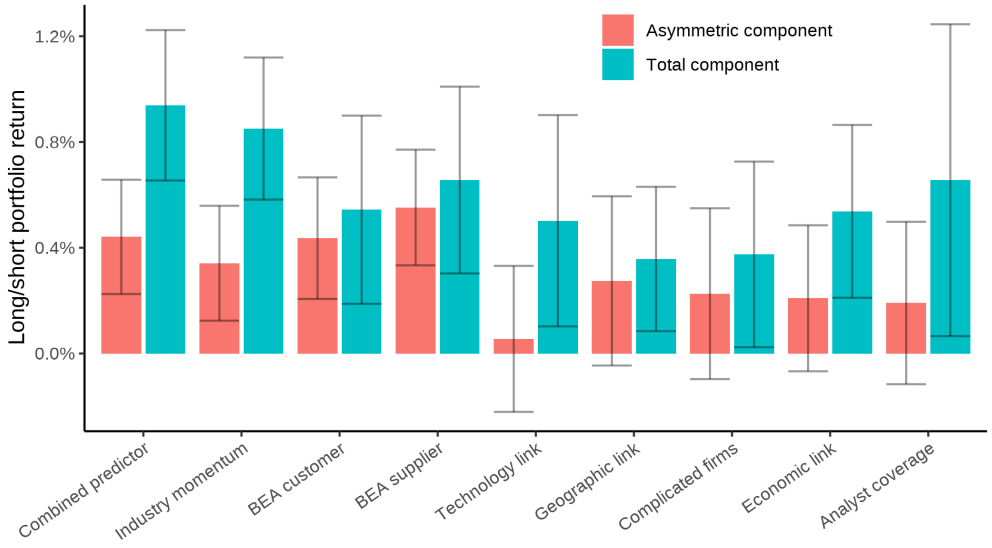
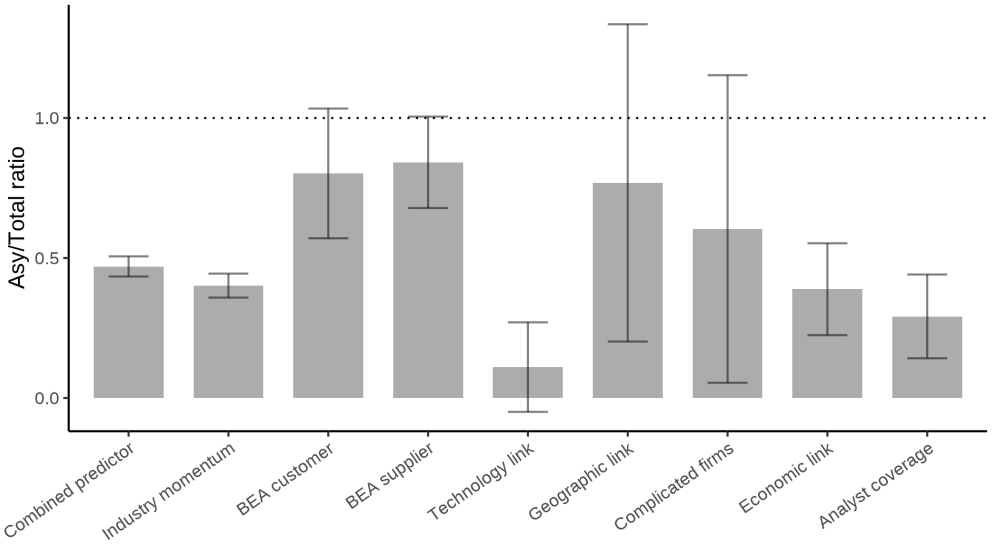


Figure 3. Detecting common components: peer versus focal portfolio returns

We compute value-weighted long–short decile portfolio returns for both focal and peer stocks sorted on the combined CSM predictor. The peer portfolio construction is explained in Section 3.1. The figure plots cumulative post-formation returns for these two portfolios, with shaded areas representing 95% bootstrapped confidence intervals.



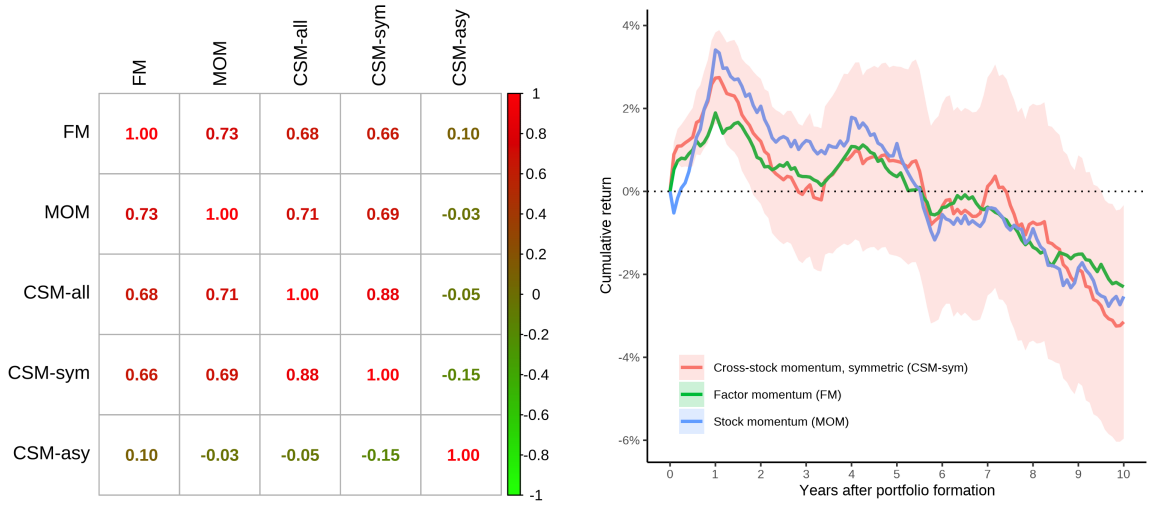
(a) Returns of total and asymmetric CSM predictors



(b) Fraction of returns due to the asymmetric component

Figure 4. Fraction of CSM returns due to the asymmetric component

For each CSM predictor, Panel (a) plots the one-month return of the value-weighted long–short decile portfolio formed on that predictor. The blue bars show returns based on the original CSM predictor, and the red bars show returns based on its asymmetric component. Panel (b) plots the ratio of one-month returns between the two, with the horizontal dashed line indicating a ratio of one. In both panels, whiskers indicate 95% bootstrapped confidence intervals.



(a) Return correlations

(b) Post-portfolio formation cumulative return

Figure 5. Relationship between CSM and other momentum portfolios

Panel (a) shows the monthly return correlations of different momentum-related portfolios: FM (factor momentum), MOM (stock momentum), and CSM (cross-stock momentum). The last two entries represent the symmetric and asymmetric components of CSM, respectively. The correlations are colored according to their values, with red (green) representing high (low) correlations. Panel (b) plots the cumulative post-portfolio-formation returns of the symmetric component of CSM, FM, and MOM. To avoid cluttering the graph, we only plot the 95% bootstrapped confidence interval for CSM as the shaded area. The sample period is 1963–2023.

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	1,931	88%	92%

Table 1. Cross-stock momentum (CSM) predictors.

The table lists the CSM predictors analyzed in this study. Column (1) lists the original academic papers and Column (2) indicates the first year that each predictor can be computed. Column (3) reports the average number of stocks 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 are covered by each predictor after it becomes available.

	Cumulative returns (%)					Standard error (%)				
Horizon:	1→1	1→12	13→60	13→84	13→120	1→1	1→12	13→60	13→84	13→120
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	0.94***	2.57***	−1.54*	−2.20**	−4.65***	(0.15)	(0.51)	(0.89)	(1.03)	(1.17)
Industry momentum	0.85***	1.92***	−1.17	−2.25**	−4.26***	(0.14)	(0.49)	(0.82)	(0.98)	(1.20)
BEA customer	0.54***	2.88***	0.36	−0.54	−3.55*	(0.18)	(0.70)	(1.33)	(1.57)	(1.87)
BEA supplier	0.66***	2.45***	1.63	0.36	−2.63	(0.18)	(0.61)	(1.20)	(1.49)	(1.70)
Technology link	0.50**	2.36***	0.25	0.02	−4.60**	(0.20)	(0.76)	(1.51)	(1.95)	(1.92)
Geographic link	0.36**	1.96***	−0.11	−1.52	−3.54**	(0.14)	(0.61)	(1.09)	(1.13)	(1.41)
Complicated firms	0.37**	0.98	−1.84*	−1.78	−5.85***	(0.18)	(0.60)	(0.94)	(1.28)	(1.58)
Economic link	0.54***	2.31***	−2.04*	−2.49*	−3.09	(0.17)	(0.73)	(1.24)	(1.50)	(1.89)
Analyst coverage	0.66**	3.45***	−1.34	−3.62*	−9.96***	(0.30)	(1.21)	(1.96)	(2.19)	(2.25)

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 $m \to n$ 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, while the last five columns report the corresponding bootstrapped standard errors. The first row displays results for the combined predictor, and the subsequent rows report results for individual predictors. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

		Cumulative returns (%)					Standard error (%)				
	Horizon:	1→1	1→12	13→60	13→84	13→120	1→1	1→12	13→60	13→84	13→120
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Full sample	Total	0.94***	2.57***	−1.54*	−2.20**	−4.65***	(0.15)	(0.51)	(0.89)	(1.03)	(1.17)
	Symmetric	0.89***	2.73***	−1.94*	−2.34**	−5.37***	(0.15)	(0.55)	(1.00)	(1.19)	(1.30)
	Asymmetric	0.44***	0.26	−0.45	0.10	0.85	(0.11)	(0.40)	(0.85)	(1.07)	(1.22)
	Asymmetric/Total	0.47***	0.10***				(0.02)	(0.02)			
1926-1962	Total	1.05***	1.83**	−2.90**	−3.79**	−3.56*	(0.24)	(0.74)	(1.37)	(1.49)	(1.84)
	Symmetric	1.03***	1.95***	−3.53**	−3.91**	−4.85***	(0.23)	(0.73)	(1.41)	(1.60)	(1.86)
	Asymmetric	0.29	0.65	−2.23*	0.00	1.93	(0.20)	(0.70)	(1.29)	(1.61)	(1.82)
	Asymmetric/Total	0.28***	0.36**				(0.04)	(0.18)			
1963-2023	Total	0.87***	3.02***	−0.66	−1.13	−5.42***	(0.18)	(0.67)	(1.19)	(1.50)	(1.65)
	Symmetric	0.81***	3.20***	−0.90	−1.29	−5.74***	(0.19)	(0.76)	(1.36)	(1.60)	(1.71)
	Asymmetric	0.53***	0.03	0.71	0.17	0.08	(0.12)	(0.50)	(1.15)	(1.38)	(1.61)
	Asymmetric/Total	0.61***	0.01				(0.04)	(0.03)			

Table 3. Decomposing CSM returns portfolios

This table decomposes CSM returns into components. Each four rows represent a group of results, with the first based on the full sample and the next two based on different subsamples. Within each group, the first three rows report the post-formation returns of value-weighted long-short NYSE decile portfolios sorted on the combined CSM predictor (in percent). "Total" refers to sorting on the original CSM predictor, while "symmetric" and "asymmetric" refer to sorting on subcomponents of the predictor. In the fourth row, "Asymmetric/Total" refers to the ratio between the asymmetric returns and total returns. The column name $m \to n$ refers to cumulative returns from month $t+m$ to $t+n$, where t is the portfolio formation month. The the last five columns report bootstrapped standard errors. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

	Peer firms							
Liquidity measure:	Bid-ask spread				Trading volume			
Focal firms	Low	Mid	High	High-Low	Low	Mid	High	High-Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	0.19	0.69***	1.13***	0.94***	0.10	0.80***	1.14***	1.03***
	(0.19)	(0.18)	(0.21)	(0.22)	(0.17)	(0.17)	(0.21)	(0.21)
Mid	0.10	0.27**	0.55***	0.45***	−0.16	0.04	0.75***	0.91***
	(0.13)	(0.13)	(0.13)	(0.16)	(0.12)	(0.11)	(0.14)	(0.18)
High	0.08	0.17	0.46***	0.37***	−0.10	−0.15	0.31***	0.41***
	(0.12)	(0.11)	(0.11)	(0.14)	(0.12)	(0.12)	(0.12)	(0.15)
High-Low	−0.10	−0.52***	−0.67***		−0.20	−0.95***	−0.82***	
	(0.19)	(0.20)	(0.20)		(0.18)	(0.19)	(0.20)	

Table 4. Asymmetric CSM return by peer and focal firm liquidity

This table reports monthly percentage returns of the asymmetric CSM predictor when restricting attention to subsets of stocks sorted by liquidity. In each cross-section, stocks are sorted into terciles by liquidity, and CSM returns are computed using only one of the terciles for peer (leader) and focal (laggard) firms. For instance, the first row of column (3) reports the case when returns of high-liquidity peer firms are used to predict returns of low-liquidity focal firms. Results in the first and last four columns measure liquidity using lagged bid-ask spreads and trading volume, respectively. The last row, as well as columns (4) and (8), report differences between portfolios. This exercise includes all U.S.-listed stocks and thus also includes small stocks that have been excluded thus far. Standard errors are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Liq measure:	Bid-ask spread			Trading volume		
	All	Liq → illiq	Illiq → liq	All	Liq → illiq	Illiq → liq
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	2.01***	2.11***	−0.10	1.65***	2.26***	−0.61***
	(0.34)	(0.41)	(0.19)	(0.39)	(0.49)	(0.23)
Industry momentum	1.98***	2.20***	−0.22	2.02***	3.15***	−1.13***
	(0.67)	(0.71)	(0.22)	(0.52)	(0.61)	(0.30)
BEA customer	3.11***	2.67***	0.44**	1.89***	2.39***	−0.50*
	(0.54)	(0.52)	(0.17)	(0.55)	(0.57)	(0.28)
BEA supplier	3.55***	2.82***	0.72***	2.71***	2.88***	−0.17
	(0.79)	(0.77)	(0.16)	(0.60)	(0.60)	(0.23)
Technology link	2.02***	1.93***	0.10	1.51***	1.83***	−0.33*
	(0.28)	(0.28)	(0.13)	(0.33)	(0.37)	(0.17)
Geographic link	0.74	0.76	−0.03	−0.88	−0.88	−0.00
	(0.77)	(0.77)	(0.10)	(0.67)	(0.65)	(0.12)
Complicated firms	−1.18***	−0.74***	−0.43*	−1.69**	−1.08*	−0.61**
	(0.45)	(0.27)	(0.22)	(0.69)	(0.56)	(0.31)
Economic link	2.20***	1.85***	0.35**	1.34***	1.64***	−0.30
	(0.34)	(0.31)	(0.14)	(0.29)	(0.34)	(0.19)
Analyst coverage	2.95***	2.95***	−0.00	2.47***	3.34***	−0.86**
	(0.32)	(0.37)	(0.19)	(0.40)	(0.56)	(0.35)

Table 5. Asymmetric CSM return, decomposed by stock-pair liquidity

Using equation (7), this table decomposes asymmetric CSM monthly returns into two components: liquid stocks leading illiquid ones, and the reverse direction. The first three and last three columns present results where stock liquidity is measured using the bid–ask spread and dollar trading volume, respectively. Columns (1) and (4) report the monthly return of the entire asymmetric CSM portfolio; differences between the two reflect sample variation due to liquidity variable availability. Columns (2) and (5) report returns from liquid stocks leading illiquid stocks, and columns (3) and (6) report returns in the reverse direction. Returns are reported in *percent*. Standard errors are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Dependent variable:	$\text{CSM}^{\text{total}}_{t+1\|t}$		$\text{CSM}^{\text{sym}}_{t+1\|t}$		$\text{CSM}^{\text{asy}}_{t+1\|t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.87***	0.44***	0.81***	0.37***	0.53***	0.49***
	(0.17)	(0.14)	(0.18)	(0.14)	(0.12)	(0.12)
$\text{FM}_{t+1\|t}$		0.73***		0.74***		0.08
		(0.05)		(0.05)		(0.06)
Obs	732	732	732	732	732	732
Adj R^2	0.00%	45.69%	0.00%	42.97%	0.00%	0.90%

Table 6. CSM spanning regressions: 1 month horizon

We estimate time-series regressions of CSM factor returns on contemporaneous FM factor returns. Columns (1) to (2), 3(0 to (4), and (5) to (6) examine the entire CSM, symmetric CSM, and asymmetric CSM components, respectively. Standard errors are reported in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Panel A: return horizon 2 to 12 months									
Dep variable:	$\text{CSM}^{\text{total}}_{t+2\to t+12\|t}$			$\text{CSM}^{\text{sym}}_{t+2\to t+12\|t}$			$\text{CSM}^{\text{asy}}_{t+2\to t+12\|t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	2.08^{***}	0.79	-0.68	2.31^{***}	1.11	-0.36	-0.52	-0.67	-0.49
	(0.72)	(0.59)	(0.50)	(0.87)	(0.69)	(0.53)	(0.53)	(0.51)	(0.52)
$\text{FM}_{t+2\to t+12\|t}$		0.78^{***}	0.35^{***}		0.72^{***}	0.29^{***}		0.09	0.14^{*}
		(0.05)	(0.06)		(0.07)	(0.08)		(0.08)	(0.08)
$\text{MOM}_{t+2\to t+12\|t}$			0.52^{***}			0.52^{***}			-0.06
			(0.05)			(0.05)			(0.04)
Obs	732	732	732	732	732	732	732	732	732
Adj R^2	0.00%	44.46%	58.20%	0.00%	33.60%	45.69%	0.00%	0.91%	1.15%
Panel B: return horizon 13 to 120 months									
Dep variable:	$\text{CSM}^{\text{total}}_{t+13\to t+120\|t}$			$\text{CSM}^{\text{sym}}_{t+13\to t+120\|t}$			$\text{CSM}^{\text{asy}}_{t+13\to t+120\|t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-5.42^{***}	-3.05^{**}	-2.02^{*}	-5.74^{**}	-4.11^{**}	-3.29^{**}	0.08	0.97	0.72
	(1.87)	(1.47)	(1.21)	(2.33)	(1.92)	(1.66)	(2.63)	(2.97)	(2.84)
$\text{FM}_{t+13\to t+120\|t}$		0.55^{***}	0.22^{*}		0.38^{**}	0.12		0.21	0.29
		(0.13)	(0.12)		(0.15)	(0.13)		(0.18)	(0.18)
$\text{MOM}_{t+13\to t+120\|t}$			0.51^{***}			0.41^{***}			-0.13^{***}
			(0.04)			(0.04)			(0.04)
Obs	624	624	624	624	624	624	624	624	624
Adj R^2	0.00%	17.93%	31.67%	0.00%	7.63%	15.69%	0.00%	2.66%	3.45%

Table 7. CSM spanning regressions: longer horizons

We estimate time-series regressions of longer horizon post-portfolio formation CSM returns on FM and MOM factor returns over the same horizons. Panel A examines returns within one year and skipping the first month after porfolio formation, while Panel B examines 10 year post-formation returns after skipping the first year. Newey-West standard errors estimated using the same number of lags as the return-forecasting horizon are reported in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

A Additional Empirical Results

A.1 Delisting

Since our results in Section 2.2 examine long-horizon returns after portfolio formation, one potential concern is that stock delisting over time might drive the observed reversals. We find, however, that the fraction of delisted stocks is very similar between the long and short portfolios, indicating that differential delisting rates do not contribute to the reversal patterns we document. Furthermore, our main results are robust to alternative treatments of delisted stocks.

[**Figure** 6 about here.]

We present results on delistings in the combined CSM predictor-based portfolio in Figure B1. Panel (a) shows the cumulative fraction of stocks that survived (i.e., were not delisted) by horizon after portfolio formation. On an equal-weighted basis, about 73% of stocks survive for ten years; on a value-weighted basis, which is more relevant to our analysis, about 87% survive. Panels (b) and (c) show survival rates for the long and short decile portfolios, which are reasonably balanced. In unreported tests, survival rates are also similar for deciles 2 through 9. These findings suggest that differential delisting rates do not meaningfully affect our long–short portfolio results.

Panel (d) recomputes cumulative long–short value-weighted CSM portfolio returns under alternative delisting treatments. The red line reproduces our baseline result from Panel (a) of Figure 1. As discussed in Section 2.2, when CRSP lacks delisting returns, we follow the literature and assume reasonable values.[20] To test robustness, the green dotted line shows results if the portfolio rotates out of stocks with missing delisting returns one month before delisting. The blue dashed line follows Hou et al. (2020), imputing missing returns from similar stocks. Results remain highly similar under both alternatives, indicating that our findings are not sensitive to delisting treatment. For brevity, figures are omitted, but the same conclusion holds for the individual CSM predictors.

A.2 Bootstrapping standard errors

To study long-horizon cumulative returns after portfolio formation, we compute standard errors using a bootstrap procedure, which we explain in this section.

[20]The fraction of stocks lacking delisting returns is very small — about 0.01% on a value-weighted basis — partly because we restrict to stocks above the 20% NYSE market capitalization cutoff. Larger stocks are less likely to have missing data.

Recall that 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 number of months after portfolio formation. In general, we are interested in computing standard errors for cumulative returns over horizons m to n, with the point estimate given by:

$$\hat{\mu}_{m,n} = \frac{1}{T}\sum_{t=1}^{T} \text{cumret}_{t+m\to t+n|t},$$
$$\text{where } \text{cumret}_{t+m\to t+n|t} = \prod_{h=m}^{n}(1+\text{ret}_{t+h|t}) - 1 \tag{8}$$

We want the bootstrap to preserve the within-vintage time-series relationship. Therefore, for each bootstrap repetition, we sample T vintages indices $\{v_1, ..., v_T\}$ with replacement from the original set of vintages $\{1, ..., T\}$. Then, we define the bootstrapped returns at horizon h for bootstrapped vintage t as:

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

Then, for each (m, n), we compute standard errors for $\text{cumret}_{t+m\to t+n|t}$ using the bootstrapped distribution of the estimator (8) where we replace $\text{ret}_{t+h|t}$ by $\text{ret}^{\text{boot}}_{t+h|t}$.

A.3 CSM reversals: robustness

This section provides further robustness checks on the main finding that CSM returns revert.

Alternative CSM portfolio construction. For comparison, Panel A of Table B1 replicates the results from Table 2. Panel B presents results using equal-weighted rather than value-weighted portfolios. Panel C reports results for value-weighted long–short quintile portfolios instead of deciles. While some variation exists across specifications, the evidence for long-term reversals remains robust.

[**Table** 8 about here.]

Symmetric–asymmetric decomposition for individual CSM predictors. Section 3 shows that for the combined CSM predictor, the symmetric component is responsible for the reversals. Figure B2 extends this analysis to individual CSM predictors.

[**Figure** 7 about here.]

A.4 Regression-based combination of CSM predictors

In the main paper, we combine individual CSM predictors by averaging them at the stock level, following Stambaugh and Yuan (2017). Alternatively, we can use a regression framework to optimally combine the predictors. This section shows that doing so does not materially change our conclusions.

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

$$r_{i,t+1} = \sum_{l=1}^{L} b_l \cdot s_{i,t}^l + \tau_t + \epsilon_{i,t+1}, \tag{9}$$

where $\{\tau_t\}_{t=1}^T$ are time fixed effects. We then construct the combined predictor using the estimated coefficients:

$$s_{i,t}^{\text{combined}} = \sum_{l=1}^{L} \hat{b}_l \cdot s_{i,t}. \tag{10}$$

The main challenge is the staggered availability of predictors. To create a complete panel, we follow Berk and Van Binsbergen (2015) and recursively impute missing predictors using others. Starting with the predictor available latest — analyst coverage, from 1983 — we regress it on the other predictors (available from 1983 onward) and use the fitted relationship to impute 1978–1982. We repeat this process for the economic link predictor (starting in 1978), and so on, until all predictors are imputed. This allows us to estimate Equation (9) on the full sample. After this recursive imputation step, we are then able to directly estimate the regression in Equation (9).

Regression results are shown in Table B2. Column (1) reports the multivariate regression; remaining columns show univariate regressions. Standard errors are clustered by time and stock. Each predictor alone significantly forecasts returns at the 1% level. In the multivariate regression, most predictors remain incrementally significant, except the Complicated firms predictor (negative and insignificant) and the BEA supplier predictor (positive and insignificant). Consistent with Ali and Hirshleifer (2020), analyst coverage has the strongest pre-

dictive power.[21] We use the estimates from column (1) to construct the regression-combined predictor per Equation (10).

[**Table** 9 about here.]

Comparison with the simple combined predictor. The regression-combined predictor is highly similar to the simple average used in the main paper. The average cross-sectional rank correlation between them is 0.95, implying they assign similar stocks to long and short portfolios. Correspondingly, all main results remain qualitatively unchanged when using the regression-combined predictor.

As an illustration, Figure B3 compares cumulative returns of the two predictors side by side. Panel (a) reproduces Panel (a) of Figure 1, showing that the long–short portfolio based on the average-combined predictor reverses over time. Panel (b) shows results for the regression-combined predictor, which are nearly identical.

[**Figure** 8 about here.]

A.5 Price-level analysis

We conduct a price-level analysis of CSM using the methodology and data from Van Binsbergen et al. (2023). We first briefly describe their approach before presenting results.

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

$$\tilde{P}_{i,t} = E_t \left(\sum_{s=1}^{J} \frac{m_{t+s}}{m_t} \cdot D_{i,t+s} + \frac{m_{t+J}}{m_t} \cdot P_{i,t+J} \right) \tag{11}$$

where $\{D_{i,t+s}\}_{s=1}^{\infty}$ are future dividends, and $P_{i,t+J}$ is the stock price J periods ahead — chosen to be a long enough horizon such that mispricings have largely dissipated. Van Binsbergen et al. (2023) set $J = 15$ years. $\{m_{t+s}\}_{s=1}^{\infty}$ is a benchmark stochastic discount factor, which they take to be the CAPM. The price wedge is then defined as the log deviation of the actual price $P_{i,t}$ from the present-value-justified price:

$$PW_{i,t} = \log \left(\frac{P_{i,t}}{\tilde{P}_{i,t}} \right) \tag{12}$$

[21] Since predictors are pre-transformed to uniform $[-0.5, 0.5]$, coefficients are comparable.

Van Binsbergen et al. (2023) estimate price wedges using a large set of characteristics-sorted portfolios, projecting them onto individual stocks. We directly use their stock-level price wedge estimates and merge them with our data, which spans 1964–2017.

Price wedge of CSM portfolio. We compute the price wedge of the combined CSM-sorted portfolio by calculating the value-weighted price wedge of long–short NYSE decile portfolios h months after formation for each portfolio formation month t:

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

We compute this measure for the total CSM portfolio as well as for its decomposed symmetric and asymmetric components.

Figure B4 shows how the price wedge evolves over different post-formation horizons. Panel (a) reports results for the combined CSM predictor, with the shaded area representing 95% Newey–West confidence intervals. In the formation month, the long portfolio appears approximately 2% overvalued relative to the short portfolio. This difference grows over the next twelve months as CSM returns materialize, then gradually reverses in subsequent years.[22] Panel (b) shows results for the symmetric and asymmetric components, indicating that the reversal is entirely driven by the symmetric component. Overall, the price wedge-based evidence is broadly consistent with our findings based on cumulative returns (Section 2).

[**Figure** 9 about here.]

A.6 Peer versus focal portfolios

Expected return patterns. Figure B5 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 consistent with Section 3.1, showing common momentum and reversals in both peer and focal portfolios. These findings suggest that CSM return reversals are driven by common movements.

[**Figure** 10 about here.]

[22] The magnitude of price wedge variation is smaller than that of cumulative CSM returns. For example, for the combined predictor, the 12-month post-formation return is 2.57% (Table 2), but the corresponding price wedge change in Panel (a) of Figure B4 is about 1%. This reflects the fact that the CSM predictors are not among the characteristics considered by Van Binsbergen et al. (2023), so their measure captures only part of the variation in CSM-sorted portfolios.

Dissecting the Peer-Focal Covariance. Section 3.1 shows that the focal and peer CSM portfolios are strongly related. In this section, we demonstrate that removing the symmetric components, as defined by the decomposition method in Section 3.3, eliminates this relationship: the remaining asymmetric components exhibit little correlation between peer and focal portfolios.

Table B3 reports the correlation between long–short decile portfolios formed from focal and peer stocks over the 10 years following portfolio formation. The first row presents results for the combined CSM predictor, showing a correlation of 0.52 between focal and peer portfolios — largely driven by the symmetric component. In contrast, the correlation between their asymmetric components is only -0.05, much closer to zero. The subsequent rows report results for individual predictors, with the final row showing the average across all eight predictors. For most predictors, removing the symmetric component substantially reduces the correlation between focal and peer portfolios. This pattern supports the interpretation that the symmetric component reflects common movements shared across firms.

[**Table** 10 about here.]

B CSM Decomposition

This section provides further details related to decomposing cross-stock momentum (CSM).

B.1 Expressing CSM predictors using prediction matrices

We provide additional detail on how various CSM predictors can be expressed using the "prediction matrix" formulation in Equation (4), which we reproduce here for convenience:

$$s_t = \Pi \cdot r_t$$

where Π is an $N \times N$ prediction matrix, r_t is a length-N vector of stock returns, and s_t is a length-N vector of CSM predictors. Below, we illustrate, through examples, how different CSM predictors can be represented in this form. We also describe the construction of the asymmetric component, defined as $\Pi_{\text{asy}} \equiv \frac{\Pi - \Pi'}{2}$, which isolates the unidirectional lead–lag relationships in these predictors.

- We begin with the simplest type of CSM predictor, industry momentum, where each stock's predictor is the value-weighted return of its own industry.

For illustration, consider an example with $N = 4$ stocks. Suppose the first two stocks belong to one industry and the remaining two to another. Assume the four stocks have market capitalizations of \$1, \$2, \$3, and \$4, respectively. The predictor can then be written as:

$$\begin{bmatrix} s_{1,t} \\ s_{2,t} \\ s_{3,t} \\ s_{4,t} \end{bmatrix} = \underbrace{\begin{bmatrix} 1/3 & 2/3 & 0 & 0 \\ 1/3 & 2/3 & 0 & 0 \\ 0 & 0 & 3/7 & 4/7 \\ 0 & 0 & 3/7 & 4/7 \end{bmatrix}}_{=\Pi} \cdot \begin{bmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \\ r_{4,t} \end{bmatrix}$$

While stocks within the same industry share the same predictor value, asymmetry in Π arises from value-weighting; if equal weights were used instead, Π would be symmetric.[23]

- The technology link and analyst co-coverage CSM predictors exhibit asymmetric components because each row of the prediction matrix is reweighted to sum to one. We illustrate this with a simple example for the technology link CSM. Suppose there are $N = 3$ stocks, and the pairwise technology similarities are:

$$c(1,2) = 0.1$$
$$c(1,3) = 0.3$$
$$c(2,3) = 0.5$$

The predictor is then defined as:

$$\begin{bmatrix} s_{1,t} \\ s_{2,t} \\ s_{3,t} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1/4 & 3/4 \\ 1/6 & 0 & 5/6 \\ 3/8 & 5/8 & 0 \end{bmatrix}}_{=\Pi} \cdot \begin{bmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \end{bmatrix}$$

The asymmetry in Π comes from the row normalization: each row is scaled so that its weights sum to one. The same logic applies to the analyst co-coverage CSM.

- Some CSM predictors are naturally asymmetric, such as the complicated firms and economic link predictors. The BEA customer and supplier predictors can also exhibit

[23] The predictor construction in this example follows Moskowitz and Grinblatt (1999). In our empirical implementation in this paper, we omit each focal stock's own return from its predictor, which introduces more asymmetry.

asymmetry if industries have non-offsetting input–output relationships. For these examples, the origin of the asymmetric components is clear; our goal here is to explain why they also exhibit symmetric components.

Consider the simplest example with $N = 2$ stocks in the economic link predictor. Suppose firm 1 is a downstream customer of firm 2. Then the predictor is defined as:

$$\begin{bmatrix} s_{1,t} \\ s_{2,t} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}}_{=\Pi} \begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix}$$

That is, the predictor uses firm 1 to forecast returns of firm 2, but not vice versa. Thus, the asymmetry is clear.

However, such return predictability can also arise from common components. As a simple example, suppose stock returns follow the statistical process:

$$r_{1,t} = f_t + \epsilon_{1,t} \tag{13}$$

$$r_{2,t} = f_t + \epsilon_{2,t} \tag{14}$$

where f_t is a common factor and $\{\epsilon_{1,t}, \epsilon_{2,t}\}$ are independent, stock-specific shocks. If f_t is autocorrelated (i.e., $\mathrm{Cov}(f_{t+1}, f_t) > 0$), then even without predictability in stock-specific components, the common factor induces a lead–lag:

$$\mathrm{Cov}(r_{2,t+1}, r_{1,t}) = \mathrm{Cov}(f_{t+1}, f_t) > 0.$$

The decomposition introduced in Section 3.2 isolates this common component. Specifically:

$$\Pi_{\text{sym}} = \begin{bmatrix} 0 & 1/2 \\ 1/2 & 0 \end{bmatrix}, \qquad \Pi_{\text{asy}} = \begin{bmatrix} 0 & -1/2 \\ 1/2 & 0 \end{bmatrix}$$

Under the statistical process defined in (14), the predictability is entirely captured by the symmetric component, while the asymmetric component carries no predictive power. To see this, note that the asymmetric predictor is:

$$\begin{bmatrix} s_{1,t}^{\text{asy}} \\ s_{2,t}^{\text{asy}} \end{bmatrix} = \begin{bmatrix} -r_{2,t}/2 \\ r_{1,t}/2 \end{bmatrix} = \begin{bmatrix} -(f_t + \epsilon_{2,t})/2 \\ (f_t + \epsilon_{1,t})/2 \end{bmatrix}$$

which does not predict returns in the cross-section. Specifically, a cross-sectional re-

gression of $r_{i,t+1}$ on $s_{i,t}^{\text{asy}}$ yields a zero coefficient in population.

- Finally, we discuss the geographic link predictor. As defined by Parsons et al. (2020), this predictor assigns equal weights to all peer stocks, where peers are firms headquartered in the same geographic area but not in the same industry. At first glance, one might expect this predictor to be symmetric due to equal weighting. However, asymmetry arises from the exclusion of same-industry peers and the row normalization.
  To illustrate, consider an example with $N = 4$ stocks. Suppose the first three stocks are headquartered in geographic area A, while the fourth is located in area B. Further, assume stocks 1 and 2 belong to the same industry, whereas stock 3 belongs to a different industry. The predictor is then given by:

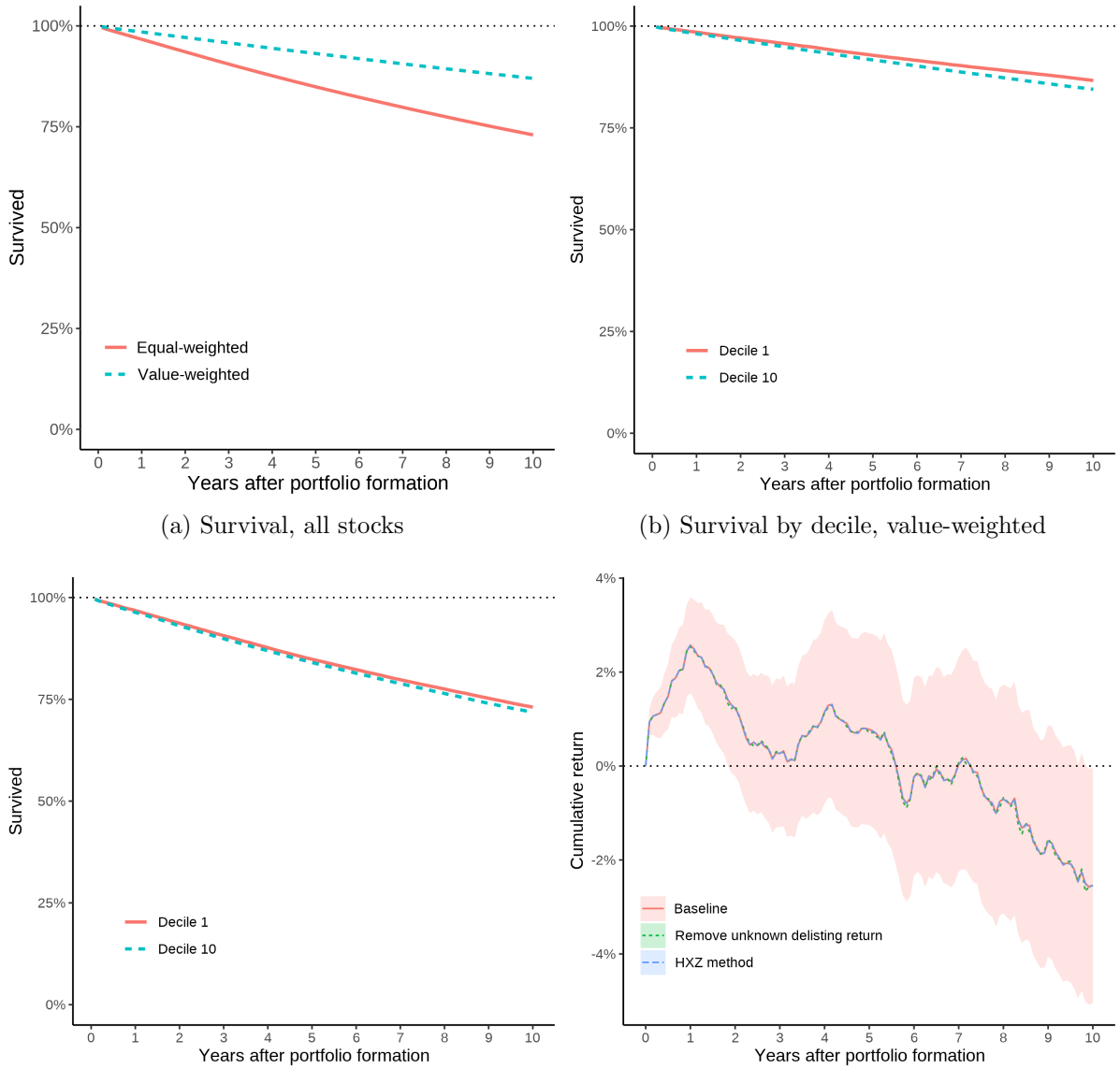
$$\begin{bmatrix} s_{1,t} \\ s_{2,t} \\ s_{3,t} \\ s_{4,t} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1/2 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{=\Pi} \cdot \begin{bmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \\ r_{4,t} \end{bmatrix}$$

  In this case, stocks 1 and 2 use stock 3 as a peer (since it is in the same geographic area but a different industry), while stock 3 uses stocks 1 and 2 as peers. However, because stocks 1 and 2 are in the same industry, they do not use each other as peers, creating asymmetry in Π.

B.2 Additional details

Table B4 reports the decomposed CSM returns for each individual CSM predictor.

[**Table** 11 about here.]



(a) Survival, all stocks

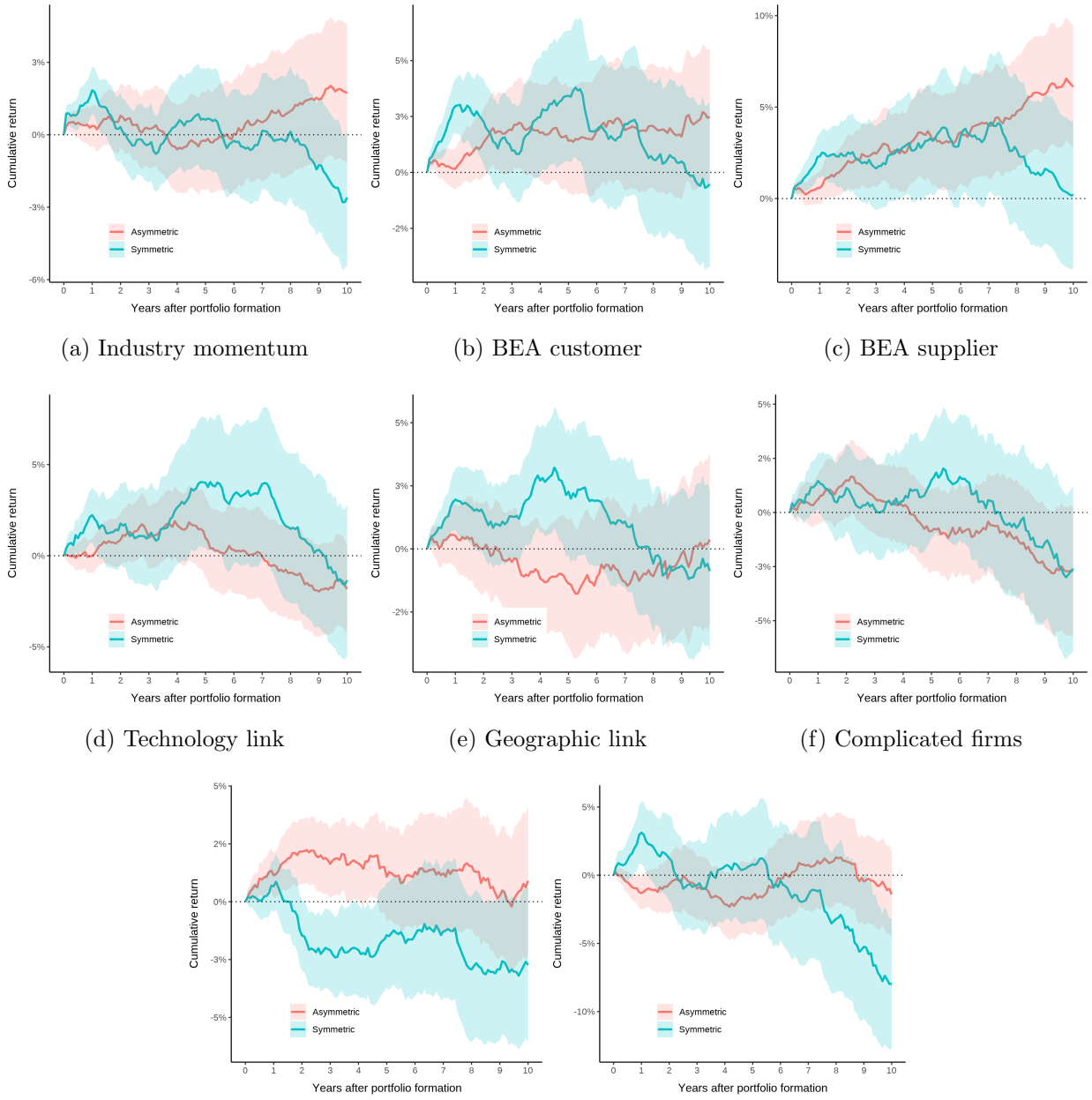
(b) Survival by decile, value-weighted

(c) Survival by decile, equal-weighted

(d) Cumulative return

Figure B1. Investigating the effect of delisting

This figure examines the potential impact of stock delisting after portfolio formation on the results in Panel (a) of Figure 1. Panel (a) of this figure plots the cumulative fraction of stocks that survive (i.e., are not delisted) after portfolio formation. 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 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% bootstrapped confidence intervals for the baseline results.



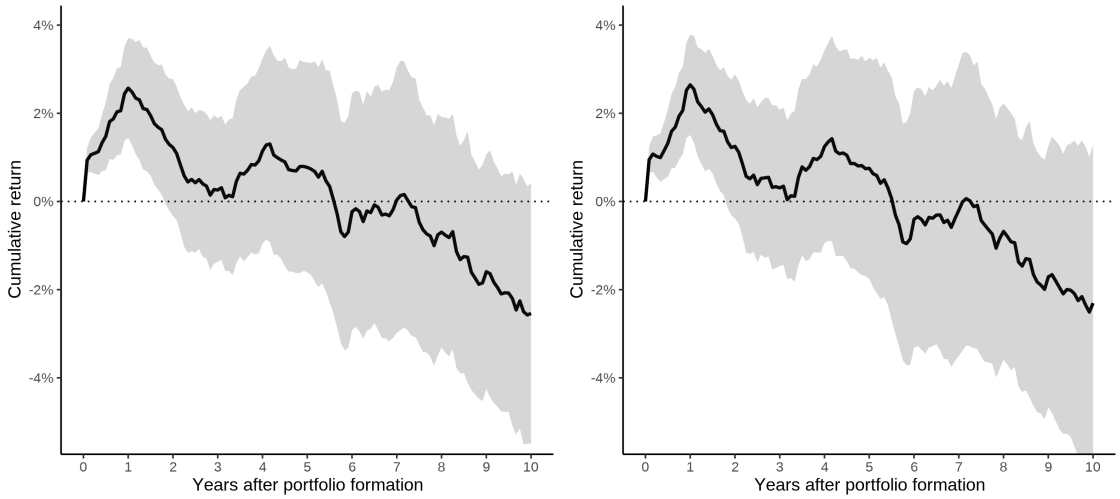
(a) Industry momentum (b) BEA customer (c) BEA supplier

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

(g) Economic link (h) Analyst coverage

Figure B2. Cross-stock momentum (CSM) decomposition: individual predictors

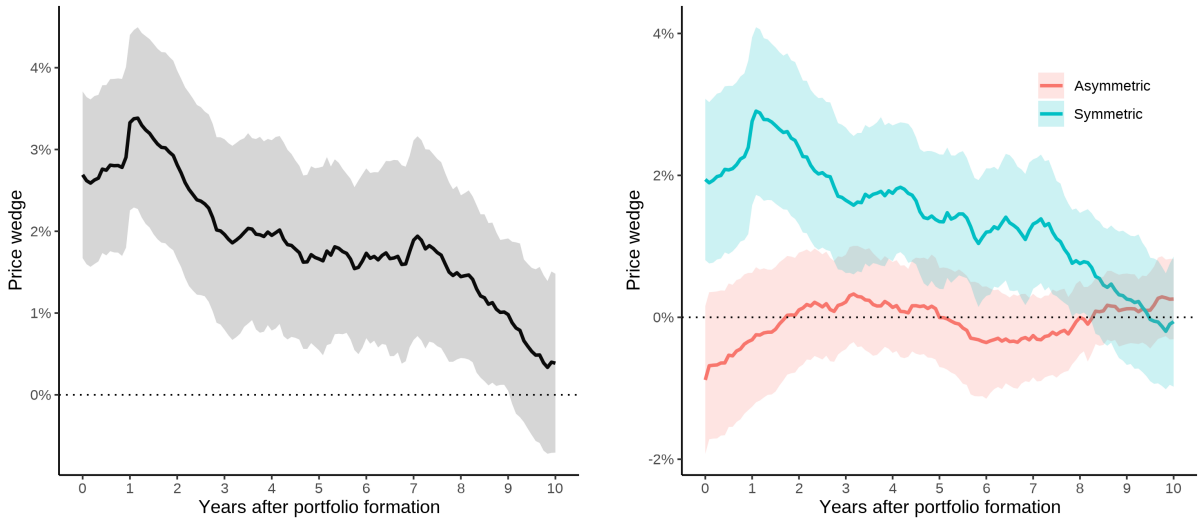
This figure plots the cumulative return of value-weighted long–short decile portfolios based on individual CSM predictors, decomposed into symmetric and asymmetric components. The decomposition method is described in Section 3.2. Shaded areas represent 95% bootstrapped confidence intervals.



(a) Average-combined predictor (b) Regression-combined predictor

Figure B3. Cross-stock momentum reversals: robustness

Panel (a) reproduces Panel (a) of Figure 1. Panel (b) conducts the same analysis while using the regression-combined predictor instead.

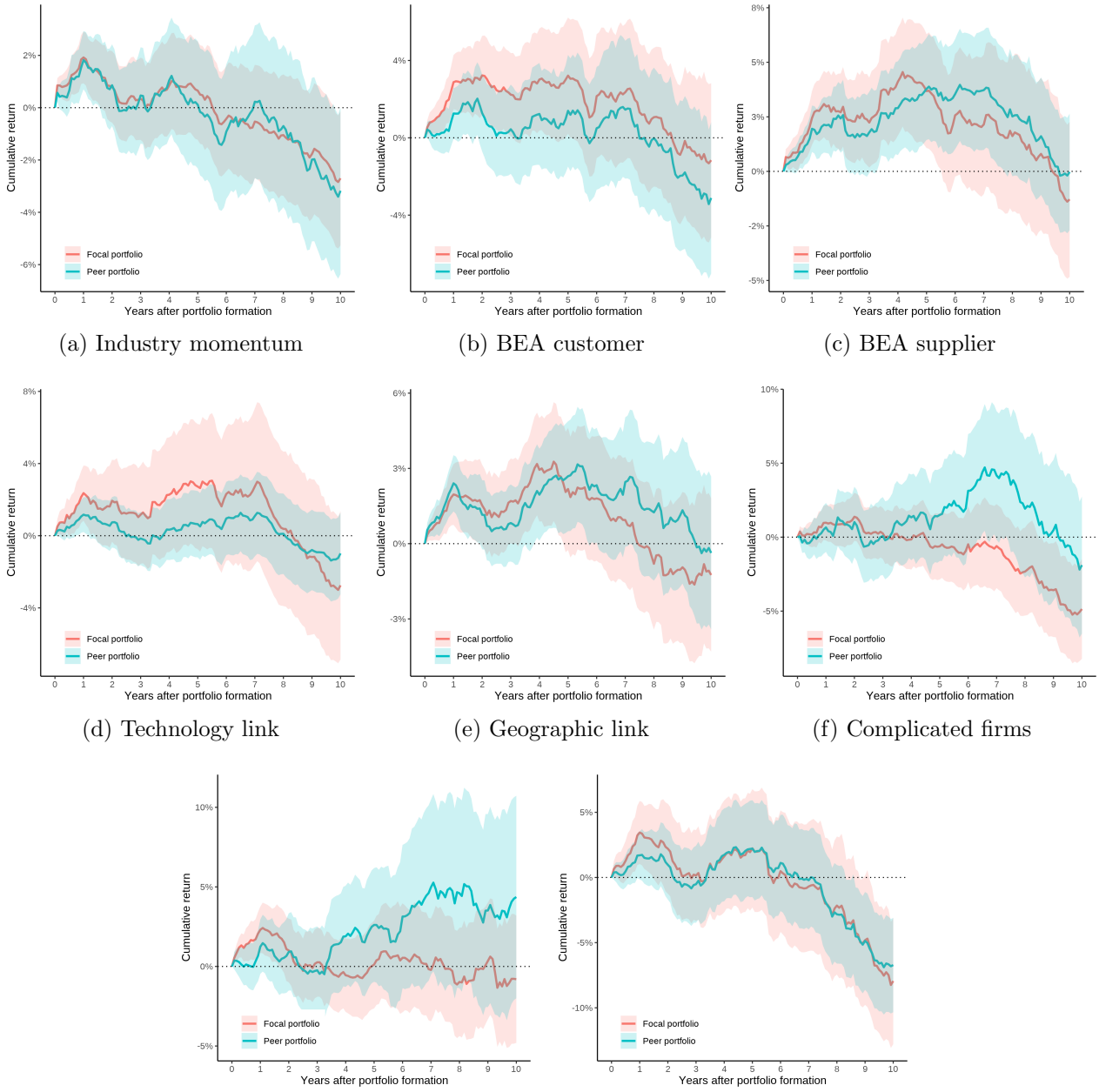


(a) Combined CSM predictor

(b) Combined CSM predictor: decomposed

Figure B4. Price wedge of CSM portfolios

We compute the value-weighted Van Binsbergen et al. (2023) price wedge — a measure of deviation from present-value-justified prices — for long–short NYSE decile portfolios sorted on the combined CSM predictor. The price wedge evolution is plotted over a ten-year horizon following portfolio formation. Panel (a) shows results for the overall predictor, while Panel (b) reports results for the symmetric and asymmetric components. Shaded areas represent 95% Newey–West confidence intervals.



(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 B5. Peer vs focal portfolios: by predictor

This figure is analogous to Panel (a) of Figure 3, but plotted separately for each individual CSM predictor.

	Cumulative returns (%)					Standard error (%)				
Horizon:	1→1	1→12	13→60	13→84	13→120	1→1	1→12	13→60	13→84	13→120
Panel A: decile portfolios, value-weighted										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	0.94***	2.57***	−1.54*	−2.20**	−4.65***	(0.15)	(0.51)	(0.89)	(1.03)	(1.17)
Industry momentum	0.85***	1.92***	−1.17	−2.25**	−4.26***	(0.14)	(0.49)	(0.82)	(0.98)	(1.20)
BEA customer	0.54***	2.88***	0.36	−0.54	−3.55*	(0.18)	(0.70)	(1.33)	(1.57)	(1.87)
BEA supplier	0.66***	2.45***	1.63	0.36	−2.63	(0.18)	(0.61)	(1.20)	(1.49)	(1.70)
Technology link	0.50**	2.36***	0.25	0.02	−4.60**	(0.20)	(0.76)	(1.51)	(1.95)	(1.92)
Geographic link	0.36**	1.96***	−0.11	−1.52	−3.54**	(0.14)	(0.61)	(1.09)	(1.13)	(1.41)
Complicated firms	0.37**	0.98	−1.84*	−1.78	−5.85***	(0.18)	(0.60)	(0.94)	(1.28)	(1.58)
Economic link	0.54***	2.31***	−2.04*	−2.49*	−3.09	(0.17)	(0.73)	(1.24)	(1.50)	(1.89)
Analyst coverage	0.66**	3.45***	−1.34	−3.62*	−9.96***	(0.30)	(1.21)	(1.96)	(2.19)	(2.25)
Panel B: decile portfolios, equal-weighted										
Combined predictor	1.20***	3.11***	−2.38***	−3.47***	−6.26***	(0.14)	(0.54)	(0.85)	(0.96)	(1.06)
Industry momentum	1.05***	2.04***	−1.79**	−2.45**	−5.48***	(0.12)	(0.48)	(0.89)	(1.01)	(1.12)
BEA customer	0.75***	3.07***	1.20	0.79	−1.36	(0.15)	(0.63)	(1.13)	(1.38)	(1.65)
BEA supplier	0.73***	2.52***	0.98	−1.01	−2.02	(0.16)	(0.67)	(1.20)	(1.29)	(1.55)
Technology link	0.77***	3.06***	−1.05	−1.28	−3.12*	(0.21)	(0.69)	(1.41)	(1.62)	(1.89)
Geographic link	0.51***	2.52***	0.29	−0.21	−2.32	(0.12)	(0.51)	(0.99)	(1.18)	(1.45)
Complicated firms	0.41***	1.90***	−1.84*	−3.40***	−6.09***	(0.13)	(0.50)	(1.08)	(1.27)	(1.43)
Economic link	0.51***	1.87***	−1.23	−2.10	−4.26***	(0.13)	(0.63)	(1.11)	(1.33)	(1.59)
Analyst coverage	1.18***	5.07***	−2.98*	−4.35**	−8.48***	(0.34)	(1.13)	(1.65)	(1.88)	(2.34)
Panel C: quintile portfolios, value-weighted										
Combined predictor	0.82***	2.16***	−0.95	−1.36	−2.99**	(0.15)	(0.50)	(0.86)	(1.03)	(1.18)
Industry momentum	0.72***	1.52***	−0.98	−1.89*	−3.26***	(0.14)	(0.50)	(0.81)	(0.97)	(1.21)
BEA customer	0.46**	2.13***	0.31	−0.17	−2.63	(0.19)	(0.66)	(1.28)	(1.49)	(1.86)
BEA supplier	0.59***	1.90***	0.99	1.06	−1.67	(0.18)	(0.65)	(1.27)	(1.57)	(1.72)
Technology link	0.55***	2.07***	−0.27	−0.29	−3.93**	(0.20)	(0.74)	(1.53)	(1.98)	(1.93)
Geographic link	0.34**	1.58***	1.06	1.19	−0.74	(0.14)	(0.60)	(1.07)	(1.09)	(1.37)
Complicated firms	0.25	0.52	−1.89**	−2.26*	−5.34***	(0.18)	(0.63)	(0.94)	(1.25)	(1.55)
Economic link	0.27	1.30*	−1.25	−0.94	−1.14	(0.17)	(0.73)	(1.22)	(1.49)	(1.83)
Analyst coverage	0.47	2.31*	−1.09	−1.87	−6.71***	(0.32)	(1.19)	(1.88)	(2.15)	(2.34)

Table B1. Alternative CSM portfolio 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.

Dependent variable: $r_{i,t+1}$ (in %)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry momentum	0.884***	1.334***							
	(0.10)	(0.15)							
BEA customer	0.353***		1.247***						
	(0.13)		(0.21)						
BEA supplier	0.146			1.046***					
	(0.17)			(0.22)					
Technology link	0.566***				1.350***				
	(0.21)				(0.29)				
Geographic link	0.354***					0.346***			
	(0.09)					(0.09)			
Complicated firms	−0.106						0.264*		
	(0.13)						(0.14)		
Economic link	0.575***							0.984***	
	(0.12)							(0.14)	
Analyst coverage	1.369***								2.001***
	(0.33)								(0.38)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	3,485,303	3,485,303	3,485,303	3,485,303	3,485,303	3,485,303	3,485,303	3,485,303	3,485,303
Within R^2	0.10%	0.05%	0.03%	0.02%	0.01%	0.00%	0.00%	0.01%	0.06%

Table B2. Combining predictors using regressions

We estimate panel regressions of next-month stock returns on individual CSM predictors, transformed to uniform $[-0.5, 0.5]$ using cross-sectional ranks. Column (1) reports a multivariate regression; remaining columns are univariate. All specifications include time fixed effects and cluster standard errors by time and stock. Missing predictor values are imputed as described in Appendix A.4. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Predictor	Return correlation		
	Total	Symmetric	Asymmetric
	(1)	(2)	(3)
Combined predictor	0.52	0.52	-0.05
Industry momentum	0.75	0.76	0.04
BEA customer	0.77	0.76	0.10
BEA supplier	0.70	0.69	-0.09
Technology link	0.80	0.79	-0.05
Geographic link	0.56	0.54	-0.36
Complicated firms	0.28	0.50	0.02
Economic link	0.26	0.18	-0.01
Analyst coverage	0.92	0.92	0.30
Average	0.63	0.64	-0.01

Table B3. Return correlations of peer and focal portfolios

As described in Section 3.1, we form long–short decile portfolios based on peer CSM stocks. The table reports the realized return correlations between focal and peer portfolios over the 10 years following portfolio formation. Column (1) shows results using the original CSM predictor; columns (2) and (3) show results using only the symmetric and asymmetric components, respectively. The first row reports the combined CSM predictor, the next eight rows report individual predictors, and the last row reports the average across all individual predictors.

		Cumulative returns (%)					Standard error (%)				
	Horizon:	1→1	1→12	13→60	13→84	13→120	1→1	1→12	13→60	13→84	13→120
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Combined predictor	Total	0.94***	2.57***	−1.54*	−2.20**	−4.65***	(0.15)	(0.51)	(0.89)	(1.03)	(1.17)
	Symmetric	0.89***	2.73***	−1.94*	−2.34**	−5.37***	(0.15)	(0.55)	(1.00)	(1.19)	(1.30)
	Asymmetric	0.44***	0.26	−0.45	0.10	0.85	(0.11)	(0.40)	(0.85)	(1.07)	(1.22)
	Asymmetric/Total	0.47***	0.10***				(0.02)	(0.02)			
Industry momentum	Total	0.85***	1.92***	−1.17	−2.25**	−4.26***	(0.14)	(0.49)	(0.82)	(0.98)	(1.20)
	Symmetric	0.88***	1.84***	−1.20	−1.38	−4.05***	(0.14)	(0.48)	(0.92)	(1.10)	(1.29)
	Asymmetric	0.34***	0.36	−0.99	−0.13	1.10	(0.11)	(0.41)	(0.90)	(1.14)	(1.37)
	Asymmetric/Total	0.40***	0.19***				(0.02)	(0.05)			
BEA customer	Total	0.54***	2.88***	0.36	−0.54	−3.55*	(0.18)	(0.70)	(1.33)	(1.57)	(1.87)
	Symmetric	0.61***	2.97***	−0.15	−1.09	−3.74**	(0.15)	(0.61)	(1.27)	(1.44)	(1.68)
	Asymmetric	0.44***	0.15	0.80	1.29	1.94	(0.12)	(0.46)	(1.02)	(1.25)	(1.43)
	Asymmetric/Total	0.80***	0.05**				(0.12)	(0.03)			
BEA supplier	Total	0.66***	2.45***	1.63	0.36	−2.63	(0.18)	(0.61)	(1.20)	(1.49)	(1.70)
	Symmetric	0.59***	2.31***	0.35	1.48	−2.15	(0.15)	(0.61)	(1.31)	(1.71)	(1.87)
	Asymmetric	0.55***	0.58	2.47**	3.50***	5.66***	(0.11)	(0.45)	(1.14)	(1.36)	(1.58)
	Asymmetric/Total	0.84***	0.24***				(0.08)	(0.04)			
Technology link	Total	0.50**	2.36***	0.25	0.02	−4.60**	(0.20)	(0.76)	(1.51)	(1.95)	(1.92)
	Symmetric	0.40**	2.23***	1.62	1.34	−2.93	(0.19)	(0.76)	(1.60)	(1.91)	(2.02)
	Asymmetric	0.06	−0.01	0.95	0.15	−1.36	(0.14)	(0.47)	(1.01)	(1.19)	(1.24)
	Asymmetric/Total	0.11	−0.01				(0.08)	(0.04)			
Geographic link	Total	0.36**	1.96***	−0.11	−1.52	−3.54**	(0.14)	(0.61)	(1.09)	(1.13)	(1.41)
	Symmetric	0.33**	1.96***	0.05	−1.45	−3.29**	(0.14)	(0.61)	(1.08)	(1.15)	(1.46)
	Asymmetric	0.27*	0.53	−2.12*	−1.77	0.30	(0.16)	(0.63)	(1.09)	(1.31)	(1.64)
	Asymmetric/Total	0.77***	0.27**				(0.29)	(0.11)			
Complicated firms	Total	0.37**	0.98	−1.84*	−1.78	−5.85***	(0.18)	(0.60)	(0.94)	(1.28)	(1.58)
	Symmetric	0.42**	1.46**	−0.27	−1.33	−4.08**	(0.21)	(0.65)	(1.11)	(1.38)	(1.80)
	Asymmetric	0.23	0.61	−1.37*	−0.89	−3.06**	(0.16)	(0.57)	(0.82)	(1.03)	(1.45)
	Asymmetric/Total	0.60**	0.62				(0.28)	(0.47)			
Economic link	Total	0.54***	2.31***	−2.04*	−2.49*	−3.09	(0.17)	(0.73)	(1.24)	(1.50)	(1.89)
	Symmetric	0.20	0.67	−2.12**	−2.04	−3.45**	(0.15)	(0.55)	(1.06)	(1.35)	(1.57)
	Asymmetric	0.21	1.14**	0.24	0.29	0.04	(0.14)	(0.49)	(0.91)	(1.21)	(1.61)
	Asymmetric/Total	0.39***	0.50***				(0.08)	(0.07)			
Analyst coverage	Total	0.66**	3.45***	−1.34	−3.62*	−9.96***	(0.30)	(1.21)	(1.96)	(2.19)	(2.25)
	Symmetric	0.61**	3.12***	−2.13	−3.77*	−9.41***	(0.31)	(1.14)	(1.89)	(2.21)	(2.25)
	Asymmetric	0.19	−1.31**	−0.38	1.98	0.47	(0.16)	(0.61)	(1.23)	(1.61)	(1.65)
	Asymmetric/Total	0.29***	−0.38***				(0.08)	(0.05)			

Table B4. Decomposing CSM returns: by individual predictor

This table is similar to Table 3, except it reports full-sample results by individual CSM predictors. Each group of four rows presents results for a specific CSM predictor using the full available sample. Within each group, the first three rows report the post-formation returns (in percent) 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 its subcomponents. The fourth row, "Asymmetric/Total," reports the ratio of asymmetric to total returns. Column labels $m \to n$ indicate cumulative returns from month $t+m$ to $t+n$, where t is the portfolio formation month. The last five columns report bootstrapped standard errors. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.