Investment Base Pairs

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Abstract

What if the sprawling complexity of signal-driven cross-sectional (CS) investment strategies could be distilled into elemental units that unlock their hidden dynamics? We confront the enduring puzzle of why these strategies—spanning value, momentum, and carry across equities, bonds, currencies, and commodities—defy traditional asset pricing models with unpredictable returns. We propose a novel decomposition into signal-driven "base pair" portfolios, exposing five pivotal drivers: own- and cross-asset predictability, signal correlation, and signal mean and variance imbalances. Using a dataset of 1,710 futures pair portfolios, constructed as motivated by our theory from widely used data spanning 1985 to 2023, we show that this framework robustly describes and predicts the cross-section of base pairs. Selective base pair targeting triples benchmark CS strategy performance at fixed leverage, pruning "junk" pairs to challenge conventional wisdom, prompting a reevaluation of asset pricing anomalies.

Keywords: own-asset effects, cross-asset effects, cross-signal correlation, signal bias, predictability, pairs trading, futures and forwards, signal sorting, investments, portfolio construction, value, momentum, carry
JEL: classification G10, G11, G12

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1. Introduction

In biology, life's complexity unfolds from the elegant simplicity of DNA's base pairs—pairs of A, T, C, G—where each pair contributes to a larger sequence, and "junk" segments are pruned to enhance function. Imagine applying this principle to finance: what if the intricate world of signal-driven long-short investment strategies—across equities, bonds, currencies, and commodities—could be decoded into elemental units that reveal their underlying mechanics? We propose that every cross-sectional (CS) strategy, which sorts assets by signals like value, momentum, or carry, can be broken into a sum of signal-driven "base pair" strategy portfolios spanning the strategy's universe. By isolating these pair portfolios, we uncover the drivers of performance, revealing insights that aggregate sorting obscures, much like decoding a genetic sequence to understand its function. Our base pairs framework offers a unifying lens to explore a diverse investment landscape, bridging theory, empirics, and practice to unlock a new understanding of financial markets.

Signal-driven CS strategies, which rank assets by metrics such as price-to-book (value), past returns (momentum), or yield differentials (carry), have been studied by academics and widely adopted by investors. The idea behind aggregate signal sorting in CS strategies is a natural one. If the level of an asset's signal is correlated with its subsequent return (e.g., greater earnings-to-price ratios having the tendency of being followed by greater returns), then greater (lesser) signal levels warrant greater (lesser) investment. In the long–short CS context, asset weights reflect relative signal strengths, and short positions are equal in magnitude to long positions. Some aggregate sorting methods cluster longs and shorts by discrete cutoffs, such as quantiles or fixed counts—e.g., "30-40-30" goes long (short) the top (bottom) 30% and neutral the middle 40% (Fama and French, 1993)—ignoring signal differences within clusters. Qualitatively similar, traditional continuous methods, such as linear-in-signal or linear-in-rank weighting, lean into the hypothesis of signal-based allocation and vary the magnitude of positions within the long and short legs according to relative signal strength.

Despite decades of study, the theoretical unity of these diverse strategies has been elusive and it remains unclear why their returns vary significantly across asset classes, signals, and

time periods.[1] Moreover, the performance of these investing styles has faced intense scrutiny in recent decades, with the literature debating whether these strategies remain viable. These concerns highlight the challenge of understanding the underlying mechanisms that drive performance, especially when traditional asset pricing models like the CAPM or Fama and French's (2015) five-factor model leave significant return variation unexplained.

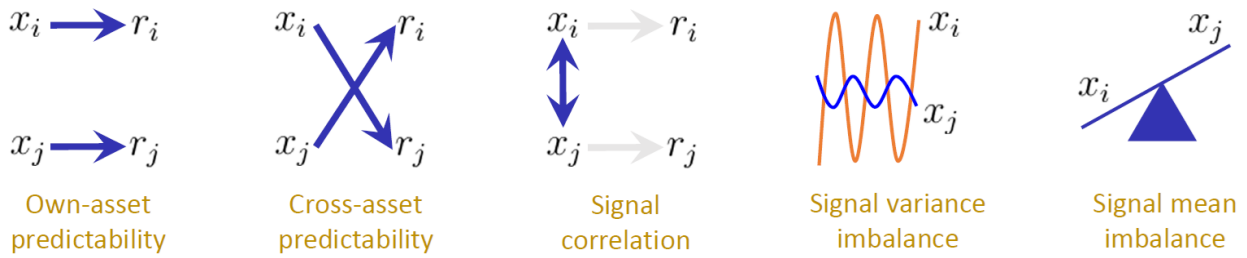
Our framework tackles this challenge by shifting focus to signal-driven pair portfolios. To fix ideas, we work with a benchmark that is linear in the rank of its assets' signals.[2] We start with a theoretical decomposition: any CS strategy with weights linear in signal ranks is the *sum of all possible signal-driven pair strategy portfolios* within its asset set (Theorem 1, Section 2). Two implications emerge from this decomposition. First, the benchmark aggregates the contributions of all pairwise interactions. These interactions include each asset's signal not only correlating with its subsequent return (own-asset effect), but also potentially correlating with the other asset's signal and return (cross-asset effect); and signals having persistence differences in average levels or variability. Second, by investing in the benchmark, one either (tacitly) assumes that there is not any significant performance variation among pair strategies, thus invests in them all; or, that if significant variation exists, it cannot be detected and exploited. What heterogeneity is masked and what performance drivers are obscured by aggregate sorting? Should we be investing in *all* pair strategies, or can we decode their genetics and prune the junk pairs?

These questions prompt a deeper inquiry into pair-level dynamics, for which we develop a simple pair strategy model. At its core, a pair strategy seeks to exploit return gaps between two assets as predicted by their relative signal gaps. Whether both assets increase in value, decrease in value, or move in opposite directions, what matters is whether signal levels time return gaps. To capture core signal-return interactions within a pair, we model each asset's return as a linear function of its own signal and that of its pair asset, plus noise, where signals and noise are jointly normally distributed. The pair's strategy return depends nonlinearly and dynamically on which signal is greater each month, going long the asset with the greater signal and short the asset with the lesser signal. Asset return intercepts, own-signal betas, and cross-signal betas govern pair-level unexplained, own-asset, and cross-asset

[1] See Figure 4, Section 3.6 and Tables D.8, D.9, D.10, D.11 in Appendix D.

[2] While there are numerous versions of top-down rank-based strategies (we discuss some alternatives in Sections 1.1 and 3.6), our choice well illustrates how signal-return dependencies govern strategy performance.

Figure 1: Five Drivers of Signal-Driven Pair Strategy Portfolios



Notes: This figure illustrates the five drivers of signal-driven pair strategy portfolio returns: own-asset predictability, cross-asset predictability, signal correlation, signal mean imbalance, and signal variance imbalance. x_i and x_j denote the signals on assets i and j at date t, respectively, with r_i and r_j denoting their returns at date $t+1$. The blue arrows indicate correlations. The waves (orange and blue) indicate time-variation in signals. The blue wedge indicates systematic differences in the levels of the signals. Each driver reflects a distinct mechanism influencing performance, as derived in Section 2.

effects, respectively. These effects manifest in the derivation of the pair's expected return, captured by Theorems 2 and 3.

Figure 1 depicts five intuitive drivers, implied by our model, that illuminate the mechanics of pair strategy performance across diverse settings: two direct drivers (D1) own-asset predictability and (D2) cross-asset predictability; and three indirect drivers that modulate the direct ones (D3) signal correlation, (D4) signal-variance imbalance, and (D5) signal-mean imbalance.[3] Let x_i and x_j denote the signals on arbitrary assets i and j at date t, respectively, and r_i and r_j denote their subsequent returns at date $t+1$—time subscripts are suppressed for brevity.

1. (D1) Own-Asset Predictability: The correlation between an asset's signal and its own subsequent return (e.g., blue arrow from x_i to r_i) measures predictive reliability: i.e., greater signal levels indicate greater asset return potential. More predictive reliability in a pair's signals contributes to return gap timing in a pair's long–short performance (e.g., $x_i > x_j$ tends to predict $r_i > r_j$).

2. (D2) Cross-Asset Predictability: Although an asset's signal should predict its own return, it might also predict the other asset's return. If cross-asset correlation (e.g., blue arrow from x_i to r_j) is stronger than own-asset correlation, the signal difference could orient the return difference in the "wrong" direction (e.g., $x_i > x_j$ tends to predict $r_i < r_j$).

3. (D3) Signal Correlation: The correlation between signals (e.g., blue arrow between x_i

[3] We also isolate the role of unexplained effects, which stem from those parts of asset mean returns unattributable to information in signals, whose manifestation in the model depends on (D5).

and x_j) determines the frequency of signal gaps. Lesser or negative correlations create larger gaps on average, which could enhance return difference potential; whereas, highly correlated signals that align often could weaken return difference opportunities (e.g., $x_i \approx x_j$ leads to $r_i \approx r_j$).

4. (D4) Signal Variance Imbalance: Differences in signal volatility levels between assets (e.g., x_i's wavier dynamics) create biases such that one asset will tend to orient the long–short positioning for the pair (e.g., $\text{sign}(x_i - x_j) \approx \text{sign}(x_i)$), which can suppress the predictability properties of its pair asset from contributing to pair portfolio performance.

5. (D5) Signal Mean Imbalance: Differences in average signal levels between assets (e.g., x_i tipping the seesaw) create biases such that one asset will systematically be long or short more often than the other, which can overshadow dynamic signal information, and lead to unexplained effects of asset means that are not attributable to signal-return predictability.

Our theory encapsulates these diverse drivers into two pair-level scores: $\overline{\theta}$, which represents *unconditional* steady-state expected return for a pair strategy for which we can test model descriptive fit; and θ, which represents *conditional* expected return for which we can test model predictive fit.[4] To carry out these tests, we construct and analyze a dataset of 1,710 signal-driven pair strategy portfolios, built from 64 liquid futures and forwards markets across four asset classes and three signal types: 15 equity indices, 13 bonds, 9 currencies, and 27 commodities (Section 3.1).[5] The data spans January 1985 to September 2023. Given low transaction costs, high liquidity, and substantial histories of these futures, this dataset provides a rich setting to study the diversity of signal-driven investing, covering 12 major strategy categories—Equity Value, Bond Value, Currency Value, Commodity Value, Equity Momentum, Bond Momentum, Currency Momentum, Commodity Momentum, Equity Carry, Bond Carry, Currency Carry, Commodity Carry—and several aggregate categories by asset class, signal type, and also an "All" category.[6]

[4] We fix leverage across strategies for all our analyses, so that portfolio returns can be interpreted as return per unit of leverage for comparability.

[5] For an asset class with N assets, there are $N(N-1)/2$ asset pairings: 105 equity pairs, 78 bond pairs, 36 currency pairs, and 351 commodity pairs. With three signal types per asset, these totals triple, and add to 1,710.

[6] Futures markets offer distinct advantages over traditional assets. Transaction costs below 5 basis points and high liquidity enable global trading efficiency. Embedded leverage amplifies returns uniquely (Erb and Harvey, 2006) and allows for standardizing leverage to ensure fair strategy comparisons. Leverage constraints outweigh volatility targets, fixing capital via margins (Moskowitz et al., 2012), and shifting focus from Sharpe ratios—limited by fixed leverage—to average returns per unit of leverage, with volatility tracked

The average monthly return for these pair portfolios is positive within all groups, which we expect to find because, in part, these are asset-class–signal-type combinations that have "worked" historically. Their typical average monthly returns, however, are relatively small in magnitude (0.19%), which highlights the problem of the benchmark CS strategy investing in all of them equally. Moreover, there is wide variation in both average monthly returns (-1.72% to 2.27%) and volatilities (0.33% to 17.71%) overall, as well as within and across subgroups. While variation across asset classes corresponds roughly with expected asset-class volatility differences, variation within asset classes—and further variation both within and across signal types—is the heterogeneity that we seek to explain.

Empirical tests in Section 3.3 confirm the model's explanatory power for the cross section of pair portfolio performance. In panel regressions, we find strong validation of the model: across 126,286 observations, our empirical counterpart to the model's steady-state pair strategy return, $\overline{\theta}$, contemporaneously explains 63.7% of long-term average return variation, with a highly significant beta of 0.984 (p-value ≈ 0) and a tiny intercept of 0.0008. A beta near 1 and a negligible intercept suggest that $\overline{\theta}$ captures the long-term average return cross section at the broadest group level approximately 1:1, with only about one-third of the variation not captured by our model.

Turning to the drivers of return variation, we find that pair portfolios are not just heterogeneous in performance, they are also very heterogeneous in what drives them. For example, own-asset effects contribute 37-51% across most groups, but range from 34.9% in Equity Carry to 83.1% in Currency Value. Cross-assets effects contribute 32-49% across most groups, but range from 14.0% in Currency Value to 54.6% in Bond Carry. Signal biases and high signal correlations drive many strategy categories through unexplained effects—linked to model intercepts—the parts of their assets' mean returns not attributable to signal predictability. In particular, Commodity Carry, Currency Carry, and Commodity Momentum are highly influenced by unexplained effects of asset means. Cross-asset and unexplained effects are both overlooked by the signal-sorting paradigm of standard CS signal-driven strategies.

Can we use these insights to predict pair strategy performance? Fama-MacBeth regres-

separately. Diverse risk exposures—geopolitical, policy, trade—enhance diversification, while aggregation in futures amplifies anomalies like momentum, value, and carry.

sions of pair portfolio monthly returns at $t+1$ against our conditional expected return metric, θ, and loadings on popular factor models, show predictive strength for θ, with a highly significant coefficient of 0.158 (t-statistic of 3.69). This coefficient also shows significant economic impact of 3.35% annualized return separation between pair portfolios that differ in their θs by two standard deviations, which is 147% relative to the average pair portfolio performance. We also include fixed effects of asset class and signal type, which improve model fit (higher R^2), suggesting they capture important heterogeneity, but θ's coefficient only reduces to 0.150, remaining highly significant (t-statistic of 3.57).

We also test the independent predictability of θ's components (unexplained, own-asset, and cross-asset effects), replacing θ in the regression, allowing for uneven contributions from each component to be estimated from the data rather than imposed by the theoretical structure. Interestingly, the overlooked components of the sorting-based approach in the benchmark strategy drive predictability while the own-asset effect is not a significant predictor. The cross-asset effect is highly predictive (coefficient of 0.161, t-statistic of 4.95), while the unexplained effect is significant at the 5% level, highlighting the inability of aggregate sorting to work out complex pair interactions. Excluding unexplained and own-asset effects, however, reveals that the predictability of the cross-asset effect alone is weak—and controlling for the average levels of other components is important to its role.

Applying these insights, we refine CS strategies by culling "junk" pairs and selecting high-performing signal-driven pair portfolios based on their θ score each month at the time of portfolio formation so there is no look-ahead bias. We carry out historical simulations over a 20-year evaluation period in which data for most signals and assets are available and report base pair selectivity gains across virtually all strategy categories and group levels. For example, Equity Value's benchmark strategy has an average return of 3.6% (annualized), but as selectivity increases (including fewer junk pairs and higher θ pairs), performance increases nearly four-fold to 14.3% at the 5% selectivity level; i.e., including only the top 5% base pairs each month. Volatility also rises with more selectivity because of concentration effects, but Sharpe ratios still increase with more selectivity despite uniform leverage constraints. Notably, several momentum strategies, which were weak or losing strategies under the benchmark approach, are converted into strong performers through base pair selectivity. For example, Equity Momentum loses -0.6% under the benchmark approach, but gains 12.4% (annualized) under the base pairs approach. For the All Portfolio group, average returns at

5% selectivity tripled relative to the benchmark. Marked selectivity gains also manifest consistently in sub-samples over the last 20, 15, 10, and 5 years of our sample for virtually all strategy categories and group levels. These gains, all at fixed leverage for comparability, demonstrate the framework's potential.

Our findings bear important implications for asset pricing theory. First, interactions between assets, alongside disparities in signal averages and volatilities, expose underlying forces that conventional approaches miss, hinting that returns may partly reflect signal design rather than pure risk compensation. Our approach shifts attention from broad signal rankings to relational dynamics, under a cohesive view across a diverse space. Second, our findings sharpen the contrast between observed performance and what traditional models predict, raising deeper questions about what drives these gains. We find that systematically filtering out underperforming pair portfolios amplifies benchmark CS strategy returns under consistent leverage. This new evidence counters concerns about the viability of these strategy categories while providing new insights on sources of their heterogeneity. Sustained performance gains across diverse subsets and types affirm these strategies' enduring strength, pointing to an overlooked element absent from existing theories.

1.1. The Setting

The exploration of investment strategies in futures and forwards markets—such as equity, bond, currency, and commodity asset domains with signal types such as value, momentum, and carry—constitutes a vibrant and substantial area of financial inquiry. Influential equity studies like Fama and French (1992) and Carhart (1997) laid the groundwork, tilting weights toward value and momentum signals, a practice extended to futures by Asness et al. (2013), who rank multi-asset contracts (equity, bond, currency, commodity) by value and momentum for long–short positions, and Koijen et al. (2018), who scale weights by carry signals. In commodities, Erb and Harvey (2006), Miffre and Rallis (2007), and Szymanowska et al. (2014) rank futures by momentum and carry, while Garcia-Feijoo et al. (2015) apply value metrics; currency forwards leverage carry Menkhoff et al. (2012), Lustig et al. (2011), and momentum Kroencke et al. (2014), and bond futures use carry Baz et al. (2018) and value Durham (2016). Baz et al. (2015) document and compare performance across all of these asset class and signal type dimensions using fixed-N signal-sort weighting. This pervasive signal-to-weight mapping, spanning equity futures Israel et al. (2018), Geczy and Samonov

(2017), to multi-asset portfolios Moskowitz et al. (2012), underscores a robust framework for capturing risk premiums.

The performance of these investing styles, however, has faced intense scrutiny in recent decades, with the literature debating whether these strategies have deteriorated or remain viable. Harvey et al. (2016) argue that some were never viable, but were discovered because researchers failed to adjust cutoffs for an obvious multiple testing problem. Value investing's struggles have sparked claims of its demise, with Fama and French (2023) documenting a weakened premium post-2000 (e.g., HML factor returns dropping from 4.8% to 0.3% annually post-2007). Yet, Israel et al. (2021) and Asness (2020) argue value's unprecedented cheapness reflects a cyclical dip, not a permanent end, a stance supported by Arnott et al. (2021) and by insights like Rekenthaler (2023) who highlights its 2022 rebound (7.2% vs. growth's -29.1%). Momentum, robust historically (Asness et al., 2013), suffers infrequent crashes (e.g., -84.6% drawdown in 2009, per Daniel and Moskowitz, 2016), but adaptations like time-series momentum sustain its edge (Moskowitz et al., 2012). Carry strategies have faltered in low-rate environments post-2008 (Koijen et al., 2018).

Beyond performance, theoretical clarity has been elusive, and these strategies serve as a critical laboratory for asset pricing and portfolio construction more generally. Traditional asset pricing models struggle to explain the returns of signal-driven strategies, possibly from structure not yet understood, a gap our base pairs framework aims to address by dissecting strategies into their elemental pair portfolios.

Our focus on pair portfolios distinguishes our work from other decomposition concepts in the literature and the database we construct is unique. Base pairs enable a direct examination of signal interactions, such as cross-asset predictability and signal correlation, which get averaged out in aggregate sorts. We also provide a framework to enhance performance by selecting high-performing pair portfolios, a practical application we explore in Section 3.6. Few researchers have discussed the importance of cross-asset signal effects. An exception is Kelly et al. (2023), who study own-asset and cross-asset effects in a multiasset context with expected returns as signals, but do not examine pair portfolios—which depend nonlinearly on asset signals—nor drivers such signal correlation, signal biases, and interactions with unexplained-, own-, and cross-asset effects.

It is worth noting that our technique differs sharply from a well-known method called "pairs trading." Originating in the 1980s through the efforts of Morgan Stanley's industry

innovators and later examined by Gatev et al. (2006), pairs trading seeks to capitalize on short-lived price gaps between two stocks with a historically tight relationship, betting on an eventual return to normalcy. Our systematic approach centers on identifying enduring, systematic ties—not just between asset returns but also between predictive indicators (signals) and those returns—aligning with the broader paradigm of CS investing. Our model's signal-driven structure and normality assumptions provide a theoretical foundation for testing strategy efficacy across a large portfolio set and a diverse multi-asset universe.

2. Theory

Consider a dollar-neutral cross-sectional (CS) strategy of n assets governed by the sorting order of n corresponding signals. We denote asset i's signal at date t by $x_{i,t}$, its corresponding strategy weight at date t by $w_{i,t}$, and its return in the period from date t to date $t+1$ by $r_{i,t+1}$. We denote the strategy return from date t to date $t+1$ by r_{t+1}. For simplicity of notation, we drop the time subscripts going forward and maintain that signals $\{x_i\}$ and weights $\{w_i\}$ are at date t while returns $\{r_i\}$ and r are realized in the next period at date $t+1$, so there is no look-ahead bias in the strategy. Accordingly, the strategy return follows: $r = \sum_{i=1}^{n} w_i r_i$. Because the strategy is dollar neutral, every period some assets are long and some are short, with asset weights summing to zero: $\sum_{i=1}^{n} w_i = 0$.

In a general aggregate sorting strategy, at the beginning of each period, signals are sorted from highest to lowest and the asset weights are ordered accordingly: the assets with the highest signals are assigned the most positive weights (highest-magnitude longs) in the period, while the assets with the lowest signals are assigned the most negative weights (highest-magnitude shorts). We denote the i-th ranked signal by $x_{[i]}$ and the corresponding weight by $w_{[i]}$, such that $x_{[1]} > x_{[2]} > \ldots > x_{[n]}$ and $w_{[1]} \geq w_{[2]} \geq \ldots \geq w_{[n]}$.[7] Accordingly, $r_{[i]}$ is the return of the asset having the i-th ranked signal and the strategy return can be expressed equivalently as $r = \sum_{i=1}^{n} w_{[i]} r_{[i]}$.

Leverage is an important consideration in long–short strategies, reflecting the exposure to uncertainty from both long and short positions. Leverage and volatility are closely linked; e.g., uniform doubling of leverage will double volatility. In practice, however, leverage is

[7] We assume the signal ordering is strict, consistent with most signals used in practice as well as those used in our study, in which signal ties are rare.

often constrained rather than volatility because volatilities are not known with certainty a priori whereas leverage is deterministic. Accordingly, we normalize the magnitudes of the weights such that the strategy has unit gross exposure: the sum of the absolute values of the weights equals to one: $\sum_{i=1}^{n} |w_i| = 1$. This convention allows us to examine how a strategy utilizes its signals to generate differences in both expected returns and volatilities under uniform usage of leverage.

2.1. Benchmark Sorting Strategy

In our *benchmark* sorting strategy, each asset weight is linear in its signal rank within the n signals.[8] For example, if $n = 5$, then the highest-ranked asset gets weight $w_{[1]} = \frac{1}{3}$, the 2nd-ranked asset gets weight $w_{[2]} = \frac{1}{6}$, the middle-ranked asset gets weight $w_{[3]} = 0$, the 4th-ranked asset gets weight $w_{[4]} = -\frac{1}{6}$, and the lowest-ranked asset gets weight $w_{[5]} = -\frac{1}{3}$. Note that this strategy is dollar neutral, $\frac{1}{3} + \frac{1}{6} + 0 - \frac{1}{6} - \frac{1}{3} = 0$, and has unit gross exposure, $\left|\frac{1}{3}\right| + \left|\frac{1}{6}\right| + |0| + \left|-\frac{1}{6}\right| + \left|-\frac{1}{3}\right| = 1$. Moreover, the difference between successive weights is uniform at $\frac{1}{6}$. For general n, the weight on the asset with the highest signal is a positive scalar, $a > 0$, and the weight on the asset corresponding to each successively lower-ranked signal is $h > 0$ units smaller ($h = \frac{1}{6}$ in the example above): $w_{[i]} = a - (i-1)h$, where $a = \frac{2(n-1)}{n^2 - 1_{\{n \text{ odd}\}}}$ and $h = \frac{4}{n^2 - 1_{\{n \text{ odd}\}}}$.[9] It is straightforward to show that this allocation gives h more units of weight to each successively higher signal, is dollar neutral, $\sum_{i=1}^{n} w_i = 0$, and has unit gross exposure, $\sum_{i=1}^{n} |w_i| = 1$.[10] Accordingly, the benchmark strategy return satisfies:

$$r = \sum_{i=1}^{n} w_i r_i = \sum_{i=1}^{n} w_{[i]} r_{[i]} = \frac{2}{n^2 - 1_{\{n \text{ odd}\}}} \sum_{i=1}^{n} [n - 2i + 1] \cdot r_{[i]}. \tag{1}$$

2.2. Pair Strategies

The pair strategy on assets i and j is a long–short strategy that is long one unit in the asset with the higher signal and short one unit in the asset with the lower signal (or neutral in both if their signals coincide), depending on the signal realizations at the beginning of

[8] The literature uses a variety of signal-rank-based weighting schemes. We discuss some variations in Section 3.6.

[9] $1_{\{n \text{ odd}\}}$ is an indicator variable that equals one (zero) if the number of assets is odd (even).

[10] Note that this rank-based CS strategy has no time-varying gross leverage and is therefore purely cross-sectional, unlike CS strategies that set weights proportional to signal magnitudes.

each period. We denote its return as follows:

$$r_{ij} = \text{sign}(x_i - x_j) \cdot (r_i - r_j). \tag{2}$$

where sign(z) equals 1 if $z > 0$, -1 if $z < 0$, and 0 if $z = 0$. If $x_i > x_j$, then $r_{ij} = r_i - r_j$; otherwise, if $x_i < x_j$, then $r_{ij} = r_j - r_i$. Note that although we have suppressed time subscripts for considering a single investment period, these pair strategies are *not static* long–short pair positions. The long and short assets in each pair strategy generally change over time as their signals switch ordering. Note also that a pair strategy is dollar neutral and a nonlinear function of its signals through the sign$(\cdot)$ function.

2.3. Base Pairs

Theorem 1 (Base Pairs)**.** *The benchmark rank-based CS strategy on n assets can be decomposed exactly into the sum of all its underlying pair strategies:*

$$r = \frac{2}{n^2 - 1_{\{n \text{ odd}\}}} \sum_{i<j} r_{ij} \tag{3}$$

where r_{ij} is the pair strategy return on assets i and j in (2).

Proof of Theorem 1. See Appendix B □

Theorem 1 indicates that all possible pair strategies of the n assets are included in the benchmark sorting strategy, with a scaling constant, $\frac{2}{n^2-1_{\{n \text{ odd}\}}}$, which preserves unit gross exposure. We call this collection of pair strategies the "base pairs." This decomposition shows that we can understand the benchmark return by studying its base pairs.

2.4. Base Pairs Model

Motivated by Theorem 1, we study the anatomy of a generic base pair strategy by constructing a linear model that can capture pairwise interactions of signals and returns within a pair strategy. Let asset returns r_i and r_j be the following linear functions of their respective signals, x_i and x_j, plus mean-zero noise terms, ε_i and ε_j:

$$r_i = \mu_i + b_{ii}x_i + b_{ji}x_j + \varepsilon_i, \tag{4}$$

$$r_j = \mu_j + b_{ij}x_i + b_{jj}x_j + \varepsilon_j, \tag{5}$$

for some scalars $\mu_i, \mu_j, b_{ii}, b_{ij}, b_{ji}$, and b_{jj}. The scalars μ_i and μ_j are model intercepts reflecting the mean part of returns not attributable to signals; b_{ii} and b_{jj} are own-asset signal betas; and b_{ij} and b_{ji} are cross-asset signal betas.

Recall from (2) that the return of the signal-driven pair strategy can be expressed as $r_{ij} = \text{sign}(x_i - x_j) \cdot (r_i - r_j)$, nonlinearly dependent on the signal difference via the sign$(\cdot)$ function. We make the following standard distributional assumptions to aid tractability and obtain closed-form expressions for the expectation and conditional expectation of this pair strategy return. Let $\mathcal{N}(m, s)$ denote a normal distribution with mean m and standard deviation s. Let x_i, x_j, ε_i, and ε_j be jointly normally distributed, where $x_k \sim \mathcal{N}(m_k, s_k)$ for $k = i, j$ and $\rho_{ij} = \mathbf{Corr}[x_i, x_j]$; and where ε_i and ε_j are independent of x_i and x_j with $\varepsilon_k \sim \mathcal{N}(0, \delta_k)$ for $k = i, j$ and correlation $\rho_{\varepsilon,ij}$.

Theorem 2 (Model Expected Return)**.** *The model expected return of a base pair strategy of assets i and j satisfies the following:*

$$\begin{aligned}\mathbf{E}[r_{ij}] &= (\mu_i - \mu_j) \cdot [1 - 2\Phi(y_{ij})] \\ &+ \sum_{k=i,j} (b_{ki} - b_{kj}) \cdot [m_k(1 - 2\Phi(y_{ij})) + 2s_k \cdot \rho_{k:ij} \cdot \phi(y_{ij})],\end{aligned} \tag{6}$$

where $y_{ij} = -\frac{m_i - m_j}{s_{ij}}$ and $s_{ij} = \sqrt{s_i^2 + s_j^2 - 2s_i s_j \rho_{ij}}$ are the z-score at zero and the standard deviation, respectively, of the signal gap $(x_i - x_j)$; where $\rho_{i:ij} = \frac{s_i - s_j \rho_{ij}}{s_{ij}}$ and $\rho_{j:ij} = \frac{s_i \rho_{ij} - s_j}{s_{ij}}$ are the signal correlations of the signal gap to x_i and x_j, respectively; and where $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cumulative distribution function (cdf) and probability distribution function (pdf), respectively.

Proof of Theorem 2. See Appendix B □

Let $\overline{\theta}_{ij}$ represent the model's unconditional expected return, $\mathbf{E}[r_{ij}]$. We can decompose $\overline{\theta}_{ij}$ exactly into three components:

$$\overline{\theta}_{ij} = \overline{\text{UE}}_{ij} + \overline{\text{OA}}_{ij} + \overline{\text{CA}}_{ij}, \tag{7}$$

where

$$\overline{\text{UE}}_{ij} = (\mu_i - \mu_j)[1 - 2\Phi(y_{ij})], \tag{8}$$

$$\overline{\text{OA}}_{ij} = (b_{ii}m_i - b_{jj}m_j)[1 - 2\Phi(y_{ij})] + 2\phi(y_{ij})\frac{b_{ii}s_i^2 + b_{jj}s_j^2 - (b_{ii} + b_{jj})s_i s_j \rho_{ij}}{\sqrt{s_i^2 + s_j^2 - 2s_i s_j \rho_{ij}}}, \tag{9}$$

$$\overline{\text{CA}}_{ij} = -\left[(b_{ij}m_i - b_{ji}m_j)[1 - 2\Phi(y_{ij})] + 2\phi(y_{ij})\frac{b_{ij}s_i^2 + b_{ji}s_j^2 - (b_{ij} + b_{ji})s_i s_j \rho_{ij}}{\sqrt{s_i^2 + s_j^2 - 2s_i s_j \rho_{ij}}}\right], \tag{10}$$

reflecting the *unexplained effect* ($\overline{\text{UE}}_{ij}$) of asset means, *own-asset effect* ($\overline{\text{OA}}_{ij}$) of signal-return betas, and *cross-asset effect* ($\overline{\text{CA}}_{ij}$) of signal-return betas, respectively.

2.4.1. Unexplained Effect of Asset Means

$\overline{\text{UE}}_{ij}$ reflects the parts of mean asset returns that do not vary with the signals—i.e., model intercepts μ_i and μ_j of (4) and (5), respectively—and stems from *signal-mean bias* (difference between signal means m_i and m_j) rather than predictive strength of either asset's signal. The term $(\mu_i - \mu_j)$ in $\overline{\text{UE}}_{ij}$ is the difference of signal-return model intercepts. Its multiplier, $1 - 2\Phi(y_{ij})$, determines the sign of the difference $(\mu_i - \mu_j)$ in $\overline{\text{UE}}_{ij}$ based on signal-mean bias through the term $y_{ij} = -\frac{m_i - m_j}{s_{ij}}$. If signal mean m_i is greater than signal mean m_j, then asset i will tend to be long and asset j will tend to be short. Moreover, y_{ij} will be negative so that $\Phi(y_{ij}) < 0.5$ and the multiplier $1 - 2\Phi(y_{ij})$ is positive, and return intercept difference $(\mu_i - \mu_j)$ will be experienced more often. If m_i is less than m_j, however, then asset i will tend to be short, y_{ij} will be positive so that $\Phi(y_{ij}) > 0.5$ and the multiplier $1 - 2\Phi(y_{ij})$ is negative, and thus the opposite difference $(\mu_j - \mu_i)$ will be experienced more often. The larger the magnitude of the signal-mean bias, the higher the magnitude of the intercept difference is in $\overline{\text{UE}}_{ij}$. Note that under no signal-mean bias—i.e., if $m_i = m_j = m$—then $\overline{\text{UE}}_{ij}$ vanishes. All else equal, however, the effect of signal-mean bias, $m_i \neq m_j$, can be amplified by *signal correlation*, r_{ij}. The higher the correlation, the smaller is $s_{ij} = s_i^2 + s_j^2 - 2s_i s_j \rho_{ij}$—the denominator of y_{ij}—and so the larger y_{ij} is in magnitude. Likewise, but in the opposite direction, lesser signal correlation reduces the magnitude of y_{ij} and, therefore, the effect of signal-mean bias on $\overline{\text{UE}}_{ij}$. Thus, signal-mean bias drives and amplifies the realization of return-pair differences that stem from properties of asset mean returns unexplained by signals, although lesser signal correlation can attenuate this effect.

2.4.2. Own-Asset Effect

$\overline{\text{OA}}_{ij}$ reflects those parts of asset returns attributable to the predictability of each asset's own signal. Specifically, b_{ii} and b_{jj}, respectively, capture the betas of returns r_i and r_j with respect to their own signals (per the bivariate signal–return model of (4) and (5)), and these betas appear *only* in the $\overline{\text{OA}}_{ij}$ term of $\overline{\theta}_{ij}$. First, consider the term $(b_{ii}m_i - b_{jj}m_j)[1-2\Phi(y_{ij})]$ of (9)—call it OA_A. Similarly to $\overline{\text{UE}}_{ij}$, the multiplier $[1 - 2\Phi(y_{ij})]$ drives the sign and magnitude of $(b_{ii}m_i - b_{jj}m_j)$ contributing to OA_A. The more that asset i's average signal level m_i exceeds m_j—all else equal—the more that asset i's own-signal predictability above that of asset j influences OA_A via $(b_{ii}m_i - b_{jj}m_j)$. Likewise, but in the opposite direction, the more that asset j's average signal level dominates, the more its own-signal predictability influences OA_A via $(b_{jj}m_j - b_{ii}m_i)$. Thus, signal-mean bias also drives and amplifies the realization of return-pair differences that stem from properties of returns attributable to own-asset signal predictability differences; though, as with $\overline{\text{UE}}_{ij}$, lesser signal correlation can attenuate this effect. Note that this property can enhance or detract from performance depending on which of the assets has the stronger own-asset signal. For example, if $m_i > m_j$ and $b_{ii} > b_{jj}$, then the asset with stronger own-asset predictability will tend to boost the performance of the pair strategy and dampen the drag of the weaker asset's signal-return relationship. Likewise, but in the opposite direction, if $m_i > m_j$ but $b_{ii} < b_{jj}$, then the strength of signal j's predictability for its own asset will tend to drag against the performance of the pair strategy, which depends more often on the weaker signal-return relationship.

Second, consider the term $2\phi(y_{ij})\frac{b_{ii}s_i^2+b_{jj}s_j^2-(b_{ii}+b_{jj})s_is_j\rho_{ij}}{\sqrt{s_i^2+s_j^2-2s_is_j\rho_{ij}}}$ of (9)—call it OA_B. OA_B also involves own-asset betas, but is influenced by signal-mean bias (via y_{ij}), *signal-volatility bias* (via heterogeneity of signal volatilities s_i and s_j), and signal correlation (ρ_{ij}). Recall that $\phi(\cdot)$ is the normal pdf function, which is symmetric around zero. Signal-mean biases y_{ij} of the same magnitude, either positive or negative, will symmetrically weaken the size of $\phi(y_{ij})$, all else equal; under no signal-mean bias, $y_{ij} = 0$, the density $\phi(0) = \frac{1}{\sqrt{2\pi}}$ attains its maximum value, which also drives OA_A discussed above, to zero. Therefore, signal-mean bias manages the weight on the two additive terms OA_A and OA_B influencing $\overline{\text{OA}}_{ij}$: the greater the signal-mean bias, the more OA_A drives $\overline{\text{OA}}_{ij}$; the lesser the bias, the more OA_B drives it.

OA_B can benefit from higher own-asset predictability in either or both assets depending

on the signs of $b_{ii}(s_i - s_j\rho_{ij})$ and $b_{jj}(s_j - s_i\rho_{ij})$. Note that if there is no signal-volatility bias, i.e., $s_i = s_j = s$ for some $s > 0$, then both of these quantities are positive for positive predictability betas, $b_{ii} > 0$ and $b_{jj} > 0$, because $(s_i - s_j\rho_{ij}) = s(1 - \rho_{ij}) > 0$ (assuming only that signals are not perfectly positively correlated). Moreover, this result reveals that the lesser the signal correlation, the higher the impact of both assets' predictability betas. Therefore, OA_B has potential to capture two sources of own-asset performance gains and lower signal correlation amplifies this potential. If there is signal-volatility bias, however, then the higher an asset's signal volatility, the more its own-asset predictability governs OA_B. For example, as s_i increases, b_{ii}, the own-asset predictability of asset i, tends to dominate the numerator of the fraction in OA_B; and the denominator of y_{ij} tends to grow, driving y_{ij} closer to zero, weakening the effect of signal-mean bias and strengthening the multiplier $\phi(y_{ij})$ which is maximized at $y_{ij} = 0$. Signal correlation can amplify or weaken this effect depending on the relative magnitudes of the numerator and denominator.

2.4.3. Cross-Asset Effect

$\overline{\mathrm{CA}}_{ij}$ reflects those parts of asset returns attributable to the predictability of each asset's signal for the *other* asset's return. Specifically, b_{ij} and b_{ji}, respectively, capture the cross-asset betas of returns r_i and r_j with respect to cross-asset signals (per the bivariate signal–return model of (4) and (5)), and these betas appear *only* in the $\overline{\mathrm{CA}}_{ij}$ term of $\overline{\theta}_{ij}$. The same conclusions we reached for $\overline{\mathrm{OA}}_{ij}$ all apply for $\overline{\mathrm{CA}}_{ij}$ because of the parallels in functional form, but the effects are *reversed* because of the negative sign leading (10). Specifically, signal-mean bias also drives and amplifies the realization of return-pair differences that stem from properties of returns attributable to cross-asset signal predictability differences, with the asset that is more often long having its cross-asset beta *detract* from pair strategy performance. Lesser signal correlation tends to amplify the drag of this effect.

More importantly, however, $\overline{\mathrm{CA}}_{ij}$ can drag from higher cross-asset predictability in either or both assets depending on the signs of $b_{ij}(s_i - s_j\rho_{ij})$ and $b_{ji}(s_j - s_i\rho_{ij})$. Note that just as for $\overline{\mathrm{OA}}_{ij}$, if there is no signal-volatility bias, i.e., $s_i = s_j = s$ for some $s > 0$, then both of these quantities are positive for positive cross-predictability betas, $b_{ij} > 0$ and $b_{ji} > 0$, because $(s_i - s_j\rho_{ij}) = s(1 - \rho_{ij}) > 0$ (assuming only that signals are not perfectly positively correlated). Moreover, this result reveals that the lesser the signal correlation, the higher the drag of both assets' cross-predictability betas. Signal-volatility bias can allocate the drag

that these cross-betas have on pair strategy performance, and signal correlation can amplify or weaken this effect.

2.4.4. Unbiased Role of Effects

The special case of no signal biases, i.e., $m_i = m_j = m$ and $s_i = s_j = s$,[11] reveals the central role of own-asset predictability, cross-asset predictability, and signal correlation as drivers of performance; namely,

$$\overline{\theta}_{ij} = s\sqrt{\frac{1-\rho_{ij}}{\pi}}(b_{ii} - b_{ij} + b_{jj} - b_{ji}), \tag{11}$$

$$\overline{\mathrm{UE}}_{ij} = 0, \tag{12}$$

$$\overline{\mathrm{OA}}_{ij} = s\sqrt{\frac{1-\rho_{ij}}{\pi}}(b_{ii} + b_{jj}), \tag{13}$$

$$\overline{\mathrm{CA}}_{ij} = -s\sqrt{\frac{1-\rho_{ij}}{\pi}}(b_{ij} + b_{ji}). \tag{14}$$

First, the performance of a pair strategy is invariant to mean return properties unexplained by the assets' signals. Second, the performance is boosted by strong and positive own-asset signals and dragged by greater cross-asset signal-return comovement. Third, greater signal correlation weakens both own-asset and cross-asset effects. Bringing back signal biases can inflate unexplained asset mean contributors and amplify one asset's strengths or weaknesses for pair strategy performance, obscuring these basic sources of long–short pair strategy performance and leading to several potentially unintended consequences that signal sorting alone is likely to fail to account for and mitigate.

2.5. Model for Prediction

In this section, we construct predictive drivers of subsequent pair strategy returns by taking into account the dynamic information embedded in the direction (sign) of signal differences, which is observable at the time of portfolio formation each period.

Theorem 3 (Model Conditional Expected Return)**.** *The model conditional expected return*

[11] An early, unpublished work examined the special case of $m_i = m_j = 0$ and $s_i = s_j = 1$ (Goulding et al., 2020).

given the sign of the signal gap for a base pair strategy of assets i and j is as follows.

$$\mathbf{E}[r_{ij}|x_i > x_j] = \mu_i - \mu_j + \sum_{k=i,j} (b_{ki} - b_{kj}) \cdot \left[m_k + s_k \cdot \rho_{k:ij} \cdot \frac{\phi(y_{ij})}{\Phi(-y_{ij})} \right], \tag{15}$$

where $y_{ij} = -\frac{m_i - m_j}{s_{ij}}$ *and* $s_{ij} = \sqrt{s_i^2 + s_j^2 - 2 s_i s_j \rho_{ij}}$ *are the z-score at zero and the standard deviation, respectively, of the signal gap* $(x_i - x_j)$*; where* $\rho_{i:ij} = \frac{s_i - s_j \rho_{ij}}{s_{ij}}$ *and* $\rho_{j:ij} = \frac{s_i \rho_{ij} - s_j}{s_{ij}}$ *are the signal correlations of the signal gap to* x_i *and* x_j*, respectively; and where* $\Phi(\cdot)$ *and* $\phi(\cdot)$ *are the standard normal cumulative distribution function (cdf) and probability distribution function (pdf), respectively.*

Proof of Theorem 3. See Appendix B. □

Note that the conditional expectation for the reverse condition $x_i < x_j$, i.e., $\mathbf{E}[r_{ij}|x_i < x_j]$, can be obtained from (15) by swapping subscripts i and j everywhere, noting the symmetries $r_{ij} = r_{ji}$, $\rho_{ij} = \rho_{ij}$, and $s_{ij} = s_{ji}$, and $y_{ij} = -y_{ji}$ and $\rho_{j:ji} = -\rho_{j:ij}$.

Analogous to the unconditional model and its three-component representation of (7), define θ_{ij} (without the bar) as the model's *conditional* expected return given the trade direction indicated by the assets' signals. We can decompose θ_{ij} exactly into three components:

$$\theta_{ij} = \mathrm{UE}_{ij} + \mathrm{OA}_{ij} + \mathrm{CA}_{ij}, \tag{16}$$

where each of these components are the conditional counterparts (no bars on top) to their unconditional versions—i.e., (8), (9), and (10)—namely,

$$\mathrm{UE}_{ij} = \begin{cases} \mu_i - \mu_j & \text{if } x_i > x_j, \\ \mu_j - \mu_i & \text{if } x_i < x_j, \end{cases} \tag{17}$$

$$\mathrm{OA}_{ij} = \begin{cases} b_{ii} m_i - b_{jj} m_j + \frac{\phi(y_{ij})}{1-\Phi(y_{ij})} \frac{b_{ii} s_i^2 + b_{jj} s_j^2 - (b_{ii} + b_{jj}) s_i s_j \rho_{ij}}{s_{ij}} & \text{if } x_i > x_j, \\ b_{jj} m_j - b_{ii} m_i + \frac{\phi(y_{ij})}{\Phi(y_{ij})} \frac{b_{ii} s_i^2 + b_{jj} s_j^2 - (b_{ii} + b_{jj}) s_i s_j \rho_{ij}}{s_{ij}} & \text{if } x_i < x_j, \end{cases} \tag{18}$$

$$\mathrm{CA}_{ij} = \begin{cases} -\left[b_{ij} m_i - b_{ji} m_j + \frac{\phi(y_{ij})}{1-\Phi(y_{ij})} \frac{b_{ij} s_i^2 + b_{ji} s_j^2 - (b_{ij} + b_{ji}) s_i s_j \rho_{ij}}{s_{ij}} \right] & \text{if } x_i > x_j, \\ -\left[b_{ji} m_j - b_{ij} m_i + \frac{\phi(y_{ij})}{\Phi(y_{ij})} \frac{b_{ij} s_i^2 + b_{ji} s_j^2 - (b_{ij} + b_{ji}) s_i s_j \rho_{ij}}{s_{ij}} \right] & \text{if } x_i < x_j. \end{cases} \tag{19}$$

3. Empirics

In this section, we first assess the descriptive fit of model-implied $\overline{\theta}$, which represents unconditional steady-state expected return for a pair strategy under model assumptions, and its components. Next, we test the predictive fit of θ, which represents the conditional

expected return of a pair strategy, and its components. Finally, we construct and analyze portfolios that selectively include high θ pair strategies.

3.1. Data

We obtain returns and signals data on 64 futures and forwards markets corresponding to a dozen widely-studied long–short CS strategies across four asset classes (15 country equity indexes, 13 bonds of varying maturities across nine currency zones, 9 currency pairs with USD, and 27 commodities across six sectors) and three signal types (value, momentum, and carry) per asset class. Data are monthly beginning in January 1985 for some of the assets. For all others, we add an asset into the analysis when its return and signal data become available, and data runs through to September 2023.

To test the viability of the framework, we use standard signals that are representative of common constructions appearing in the literature. For equities, value is the earnings/price ratio (3-year z-score); momentum is the average trailing 12-month return; and carry is the futures roll (spot minus first). For bonds, value is the real yield; momentum is the average trailing 12-month return; and carry is the excess yield plus term-structure roll. For currencies, value is the 5-year real exchange rate reversal (3-year z-score); momentum is the average trailing 12-month return; and carry is the cash rate differential. For commodities, value is the 5-year price reversal; momentum is the average trailing 12-month return; and carry is the futures roll (first minus second).[12] See Appendix A for more data details.

3.2. Pairs Descriptive Statistics

Motivated by our theory, we construct a dataset consisting of a panel of empirical counterparts for our base pair model variables using rolling estimation windows by asset class: equities experience faster-moving, shorter-lived regimes than other asset classes, so we choose a rolling estimation window of 10 years; bond regimes are slower, so we choose 15-year estimation window; currency and commodity regimes are the slowest, so we choose 20-year estimation windows for each.[13] Our data construction results in 1,710 base pair portfolio

[12] A 12-month window is standard for momentum analyzed in the literature: Moskowitz et al., 2012, and Huang et al., 2020, among others. Similar to Goyal and Jegadeesh (2017) and Huang et al. (2020), 12-month momentum is defined as long one unit if the signal is positive; otherwise, short one unit.

[13] We use all available data within an estimation window, but require a minimum of 24 months of observations for each estimate. Results are robust across signal types to variation within 5-year ranges around these window choices and to 1-year variations in the minimum observations requirement.

Table 1: Summary Statistics of Signal-Driven Long–Short Pair Portfolios

	Portfolio Months	Unique Months	Unique Portfolios	Start Date	Avg. Ret. (%)	Avg. Vol. (%)	Avg. $\overline{\theta}$ (%)
All Portfolios:							
All	518,884	453	1,710	1986-01	0.19	7.401	0.16
Asset Class:							
Equity All	76,341	408	315	1989-10	0.09	3.881	0.06
Bond All	60,495	452	234	1986-02	0.06	1.466	0.03
Currency All	35,276	405	108	1990-01	0.07	2.860	0.11
Commodity All	346,772	453	1,053	1986-01	0.26	10.239	0.21
Signal Type:							
All Value	155,213	309	570	1998-01	0.14	7.403	0.11
All Momentum	202,875	453	570	1986-01	0.17	7.405	0.18
All Carry	160,796	309	570	1998-01	0.25	7.396	0.18
Strategy Category:							
Equity Value	23,343	281	105	2000-05	0.13	3.789	0.13
Equity Momentum	27,576	408	105	1989-10	0.00	4.011	-0.11
Equity Carry	25,422	309	105	1998-01	0.15	3.842	0.19
Bond Value	19,415	308	78	1998-02	0.05	1.446	0.04
Bond Momentum	21,665	452	78	1986-02	0.08	1.507	-0.01
Bond Carry	19,415	308	78	1998-02	0.05	1.446	0.07
Currency Value	10,916	305	36	1998-05	0.01	2.848	0.04
Currency Momentum	13,620	405	36	1990-01	0.06	2.894	0.11
Currency Carry	10,740	309	36	1998-01	0.14	2.840	0.16
Commodity Value	101,539	309	351	1998-01	0.17	10.275	0.13
Commodity Momentum	140,014	453	351	1986-01	0.26	10.193	0.27
Commodity Carry	105,219	309	351	1998-01	0.34	10.249	0.20

Notes: This table reports summary statistics for all long–short dollar-neutral pair portfolios constructed from monthly data across four asset classes (equity, bond, currency, commodity) and three signal types (value, momentum, carry); see Section 3.1. All portfolios have an end date of 2023-09. Portfolio Months is the total number of return observations for all pair portfolios. Unique Months is the number of distinct months with a pair portfolio return observation within the subset. Unique Portfolios is the count of distinct pair portfolios within each aggregation. Avg. Ret. is the group average of portfolio time-average returns, expressed in percentage. Avg. Vol. the group average of portfolio time-series volatility, expressed in percentage. $\overline{\theta}$ is the empirical counterpart to model equation (7), the model-implied expected return, estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Avg. $\overline{\theta}$ is the group average of the portfolio time-averaged $\overline{\theta}$.

monthly time series with the following numbers of base pairs per signal type: 105 equity pairs, 78 bond pairs, 36 currency pairs, and 351 commodity pairs. Note that our dataset focuses on common strategies in the literature, so cross-asset-class pair portfolios (e.g., equity vs. commodity) are not included.

Table 1 reports the summary statistics for our pair portfolios by various groupings. All

possible combinations of asset pairs and signal types results in a large dataset with over half a million portfolio months across more than 37 years. Throughout our study, we organize results into groups by all portfolios, asset class, signal type, and strategy category. The start dates of pair portfolios vary across and within groupings and are dictated by the start dates of the asset within the pair having the later start date. Commodity pair portfolios exhibit higher average returns and volatility, consistent with typical commodity market characteristics. Equities show mixed performance across signal types, with momentum underperforming on average. Bonds and currencies have lower volatility, with currencies showing small average returns for value signals. Carry outperforms value and momentum, on average, with approximately the same average volatility across pair portfolios.

Note that in Table 1, the average monthly return for pair portfolios is positive for all groups, which we expect to see because we study these asset-class–signal-type combinations in part because they are ones that "worked" historically. However, the typical average returns are relatively small in magnitude—which highlights the problem of the benchmark CS strategy investing in all of them equally. The last column of Table 1 reports the average value of $\overline{\theta}$, our model's description of long-term average returns over a trailing estimation window. $\overline{\theta}$ generally aligns directionally with average pair returns of Table 1, suggesting some descriptive power across categories, though not obviously more so than might be explained more simply by asset class volatility heterogeneity. Within each group, however, there is wide variation in both average return and volatility of pair portfolios, as reported in Table 2. It is this heterogeneity that we seek to understand.

3.3. Explanatory Panel Regressions

First, we assess the aggregate fit of unconditional $\overline{\theta}$ of (7) for steady-state mean returns of our 1,710 pair portfolios and then explore how the three major components, $\overline{UE}$, $\overline{OA}$, and $\overline{CA}$—of (8), (9), and (10), respectively—describe pair portfolio return variation. $\overline{\theta}_{ij}$ is designed to reflect steady-state long-term pair strategy average returns, taking into account the nonlinear impact of signal differences varying over time and the corresponding average signal-return effects (means, volatilities, and betas) from dynamically flipping long and short asset positions. Our model relies on simplifying assumptions, however, that are not likely to hold in the real world: linear return–signal relationships (own and cross-asset); joint normality; time invariance of moments; and unmodeled effects. The degree to which our

Table 2: Within-Group Percentiles of Signal-Driven Long–Short Pair Portfolios

	Avg. Ret. Percentiles (%)					Volatility Percentiles (%)				
	Min	25	50	75	Max	Min	25	50	75	Max
All Portfolios:										
All	-1.72	-0.07	0.12	0.42	2.27	0.33	3.27	8.55	10.68	17.71
Asset Class:										
Equity All	-0.78	-0.07	0.08	0.25	1.04	1.12	3.12	3.80	4.53	6.36
Bond All	-0.18	-0.03	0.04	0.14	0.55	0.33	1.11	1.38	1.70	2.90
Currency All	-0.27	-0.04	0.06	0.17	0.74	1.63	2.49	2.76	3.21	4.26
Commodity All	-1.72	-0.14	0.24	0.61	2.27	2.27	8.94	10.22	11.41	17.71
Signal Type:										
All Value	-1.72	-0.12	0.07	0.35	1.99	0.33	3.22	8.66	10.71	17.47
All Momentum	-0.97	-0.08	0.09	0.38	1.68	0.33	3.41	8.40	10.63	17.71
All Carry	-1.39	-0.03	0.17	0.51	2.27	0.33	3.22	8.66	10.70	17.46
Strategy Category:										
Equity Value	-0.35	-0.03	0.11	0.29	0.77	1.14	3.10	3.75	4.42	6.36
Equity Momentum	-0.78	-0.12	0.01	0.15	0.71	1.21	3.27	4.02	4.62	6.11
Equity Carry	-0.70	0.00	0.13	0.34	1.04	1.12	3.09	3.79	4.52	6.35
Bond Value	-0.14	-0.04	0.02	0.10	0.48	0.33	1.10	1.38	1.65	2.88
Bond Momentum	-0.18	0.00	0.09	0.16	0.34	0.33	1.13	1.41	1.77	2.90
Bond Carry	-0.18	-0.04	0.03	0.13	0.55	0.33	1.10	1.37	1.65	2.89
Currency Value	-0.21	-0.07	0.00	0.10	0.31	1.67	2.50	2.73	3.15	4.26
Currency Momentum	-0.27	-0.03	0.03	0.15	0.74	1.63	2.55	2.81	3.24	4.08
Currency Carry	-0.11	0.01	0.15	0.25	0.44	1.65	2.47	2.73	3.15	4.21
Commodity Value	-1.72	-0.25	0.14	0.54	1.99	2.41	9.02	10.22	11.40	17.47
Commodity Momentum	-0.97	-0.08	0.26	0.59	1.68	2.27	8.82	10.21	11.54	17.71
Commodity Carry	-1.39	-0.03	0.31	0.72	2.27	2.41	8.94	10.23	11.33	17.46

Notes: This table reports percentiles of portfolio-level statistics for 1,710 long–short dollar-neutral signal-driven pair portfolios constructed from monthly data across four asset classes (equity, bond, currency, commodity) and three signal types (value, momentum, carry); see Section 3.1 and Table 1. Avg. Return Percentiles are the minimum, 25th, 50th, 75th percentiles, and maximum of portfolio time-series mean return within each group, expressed in percentage. Volatility Percentiles are the minimum, 25th, 50th, 75th percentiles, and maximum of portfolio time-series return volatility, expressed in percentage.

design captures real-world signal-driven pair portfolio behavior is an empirical question. Here, we test the model's descriptive validity for pair strategy unconditional average returns, using contemporaneous panel regressions of long-term averages against unconditional $\overline{\theta}_{ij}$ over common estimation windows.

Aggregate Power of $\overline{\theta}$

We estimate the contemporaneous relationship between steady-state (trailing-window) mean portfolio returns ($\text{Avg}(r_{ij})$) and $\overline{\theta}_{ij}$, using the equation:

$$\text{Avg}(r_{ij})_t = \alpha + \beta \overline{\theta}_{ij,t} + \epsilon_{ij,t}, \tag{20}$$

across all pair portfolios ij, over all months t, where α is the intercept, β is the coefficient on $\overline{\theta}$, and $\epsilon_{ij,t}$ is the error term. It is known that correlations across various assets change over time (Erb et al., 1994, Longin and Solnik, 1995, Boucrelle et al., 1996 and Campbell et al., 2002). Accordingly, we estimate $\overline{\theta}_{ij}$ and $\text{Avg}(r_{ij})_t$ on a rolling basis over trailing windows (120 months for equity, 180 for bonds, 240 for currency and commodities), resulting in 126,286 portfolio-month observations overall. We compute Newey and West (1987) standard errors, which adjust for heteroskedasticity and autocorrelation. This procedure properly handles autocorrelated residuals that arise from mean-reversion of the slow-moving characteristic $\overline{\theta}_{ij}$, which has deep overlapping input data that includes lagged returns at every month for several trailing years; see Appendix C.

Table 3 reports these estimates across all portfolios, by asset class, signal type, and strategy. The headline finding is strongly consistent with implications of the model: across all 126,286 observations, $\overline{\theta}_{ij}$ contemporaneously explains 63.7% of return variation, with a beta of 0.984 (p-value ≈ 0) and a small intercept of 0.0008. A beta near 1 and a negligible intercept suggest that $\overline{\theta}$ captures nearly the entirety of steady-state average returns at the broadest group level, as predicted by $\mathbf{E}[r_{ij}] = \overline{\theta}$. This result is important because it shows that our model, despite its simplifying assumptions, has descriptive validity.

This validation holds for asset class groups and signal type groups, with some notable lag for carry. At the strategy level, Currency Carry stands out with an Adj. R^2 of 0.852 and a beta of 1.001, closely aligning with the model, possibly due to stable cash rate differentials in currency markets Lustig and Verdelhan (2007). Commodity Carry, however, shows weaker fit (Adj. $R^2 = 0.486$, $\beta = 0.785$). Bonds and equity strategies perform consistently well, with small intercepts reinforcing the model's accuracy. Currency Value lags while Currency Momentum overstates, but these two categories have the highest standard errors and fewer observations.

Table 3: Theta-Only Regression Results Across Portfolio Groups

	Adj. R^2	Beta ($\overline{\theta}$)	SE (Beta)	Intercept	N
All Portfolios:					
All	0.637	0.984***	0.007	0.0008***	126,286
Asset Class:					
Equity All	0.665	0.965***	0.006	0.0002***	30,981
Bond All	0.767	0.986***	0.005	0.0001***	17,175
Currency All	0.626	1.080***	0.025	0.0003***	6,788
Commodity All	0.619	0.957***	0.008	0.0014***	71,342
Signal Type:					
All Value	0.591	0.966***	0.005	−0.0001**	25,976
All Momentum	0.720	1.071***	0.006	0.0010***	71,237
All Carry	0.489	0.808***	0.006	0.0011***	29,073
Strategy Category:					
Equity Value	0.498	0.967***	0.009	0.0004***	8,223
Equity Momentum	0.679	0.991***	0.013	0.0003***	12,456
Equity Carry	0.669	0.970***	0.006	−0.0002***	10,302
Bond Value	0.778	0.981***	0.009	0.0000	4,956
Bond Momentum	0.758	1.022***	0.020	0.0002***	7,263
Bond Carry	0.789	0.965***	0.007	0.0001***	4,956
Currency Value	0.510	0.818***	0.046	−0.0002***	1,412
Currency Momentum	0.593	1.335***	0.051	0.0005***	4,116
Currency Carry	0.852	1.001***	0.010	0.0004***	1,260
Commodity Value	0.585	0.996***	0.006	−0.0006***	11,385
Commodity Momentum	0.702	1.047***	0.006	0.0014***	47,402
Commodity Carry	0.486	0.785***	0.006	0.0024***	12,555

Notes: This table reports contemporaneous panel regressions of trailing-window mean pair-portfolio returns on unconditional theta ($\overline{\theta}$) across all portfolios, by asset class, signal type, and strategy category. $\overline{\theta}$ is the empirical counterpart to model equation (7), the model-implied expected return, estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Standard errors are Newey and West (1987) HAC-adjusted; see Appendix C. Adj. R^2 measures explanatory power adjusted for degrees of freedom. Beta (θ) is the coefficient on $\overline{\theta}$, with SE (Beta) indicating precision. A beta of 1 and intercept of 0 indicates $\overline{\theta}$ fully captures average returns, per the model: $\mathbf{E}[r_{ij}] = \overline{\theta}_{ij}$. N is the number of portfolio-month observations. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Decomposing Heterogeneity with UE, OA, and CA

Table 4 shifts focus to components and their variance contributions based on the regression equation:

$$\text{Avg}(r_{ij})_t = \alpha + \beta_{\text{UE}}\overline{\text{UE}}_{ij,t} + \beta_{\text{OA}}\overline{\text{OA}}_{ij,t} + \beta_{\text{CA}}\overline{\text{CA}}_{ij,t} + \epsilon_{ij,t}, \tag{21}$$

across all pair portfolios ij, over all months t, where α is the intercept, β_k is the coefficient on component k, and $\epsilon_{ij,t}$ is the error term. Components and $\text{Avg}(r_{ij})_t$ are estimated over

Table 4: Three-Component Regression Results Across Portfolio Groups

Group	Var. $\overline{\text{UE}}$ (%)	Var. $\overline{\text{OA}}$ (%)	Var. $\overline{\text{CA}}$ (%)	N
All Portfolios:				
All	12.9	45.6	41.6	126,286
Asset Class:				
Equity All	9.7	48.1	42.2	30,981
Bond All	3.5	47.6	48.9	17,175
Currency All	28.3	39.6	32.1	6,788
Commodity All	6.3	49.0	44.8	71,342
Signal Type:				
All Value	1.3	51.1	47.7	25,976
All Momentum	10.8	48.8	40.4	71,237
All Carry	22.0	36.9	41.1	29,073
Strategy Category:				
Equity Value	12.0	45.0	42.9	8,223
Equity Momentum	3.1	51.1	45.8	12,456
Equity Carry	15.8	34.9	49.2	10,302
Bond Value	7.6	44.7	47.7	4,956
Bond Momentum	1.4	51.5	47.0	7,263
Bond Carry	2.0	43.4	54.6	4,956
Currency Value	2.9	83.1	14.0	1,412
Currency Momentum	10.1	51.2	38.7	4,116
Currency Carry	30.4	37.1	32.5	1,260
Commodity Value	0.7	50.5	48.7	11,385
Commodity Momentum	16.4	41.3	42.3	47,402
Commodity Carry	19.2	43.0	37.8	12,555

Notes: This table reports contemporaneous panel regressions of trailing-window mean pair-portfolio returns on unconditional components $\overline{\text{UE}}$, $\overline{\text{OA}}$, and $\overline{\text{CA}}$ across all portfolios, by asset class, signal type, and strategy category. Each component is the empirical counterpart to model equations (8), (9), and (10), respectively, estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Standard errors are Newey and West (1987) HAC-adjusted; see Appendix C. Variance contributions show the percentage of explained variance attributed to each component (UE: unexplained effect, OA: own-asset effect, CA: cross-asset effect), summing to 100% within each group. N is the number of portfolio-month observations. Significance of betas (not shown) are all $p < 0.01$.

trailing windows (120 months for equity, 180 for bonds, 240 for currency and commodities), and as before, we compute Newey and West (1987) standard errors, which adjust for heteroskedasticity and autocorrelation; see Appendix C.

Table 4's decomposition sheds new light on the drivers of return variation. The model anticipates $\overline{\text{OA}}$ as a key driver, reflecting the direct impact of an asset's signal on its return,

an intuitive hypothesis supported by our findings. $\overline{\text{OA}}$ consistently contributes 40–50% across most groups, peaking at 83.1% in Currency Value, likely due to the signal's focus on own-asset valuation (e.g., real exchange rate reversals).

A fascinating revelation is the important role of $\overline{\text{CA}}$, which is overlooked by a signal-sorting paradigm. $\overline{\text{CA}}$, capturing cross-asset signal spillovers, contributes notably (e.g., 54.6% in Bond Carry, 49.2% in Equity Carry), suggesting that base pair performance hinges not just on individual signals but on their interactions across assets. This finding, novel to our decomposition approach, contrasts with the focus on own-asset effects that permeates the literature, highlighting a heretofore hidden driver. $\overline{\text{UE}}$, representing baseline return differences not attributable to signals, spikes in Currency Carry (30.4%) and All Carry (22.0%).

3.4. Base Pair Drivers

In this section, we explore the empirical connections of the theoretical relationships—discussed in Sections 2.4.1, 2.4.2, and 2.4.3—between steady-state returns and five key drivers: own-asset effect, cross-asset effect, signal correlation, signal-mean bias, and signal-volatility bias. The unexplained effect, stemming from return mean properties unattributed to signals, also matters. Table 5 reports, by category, the normalized values of the pair-average unexplained, own-asset, and cross-asset effects, as well as the pair-average signal correlation, signal-mean bias, and signal-volatility bias. For each group of pair portfolios, we normalize the group's average component value (i.e., $\overline{\text{UE}}$, $\overline{\text{OA}}$, or $\overline{\text{CA}}$) as a ratio to the sum of the absolute values of the three average components; e.g., $\langle\overline{\text{UE}}\rangle = \overline{\text{UE}}/(|\overline{\text{UE}}|+|\overline{\text{OA}}|+|\overline{\text{CA}}|)$. This normalization aids comparison across groups.

Figure 2 provides a unified visualization of the way in which drivers of average pair performance manifest for strategy categories across this rich investment space. Figure 2 maps absolute values of these three normalized components into a triangle in two-dimensions, with sole reliance on just one of $|\overline{\text{UE}}|$, $|\overline{\text{OA}}|$, or $|\overline{\text{CA}}|$ as each corner of the triangle. The closer a strategy category is to a corner, the more it relies on the component associated with that corner.

We measure signal-mean bias (cf., Section 2.4.1) as the absolute value of the ratio of the mean of a pair's signal difference to the standard deviation of its signal difference; i.e., $\left|\frac{m_i - m_j}{s_{ij}}\right|$. This metric can be interpreted as the number of standard deviations that the

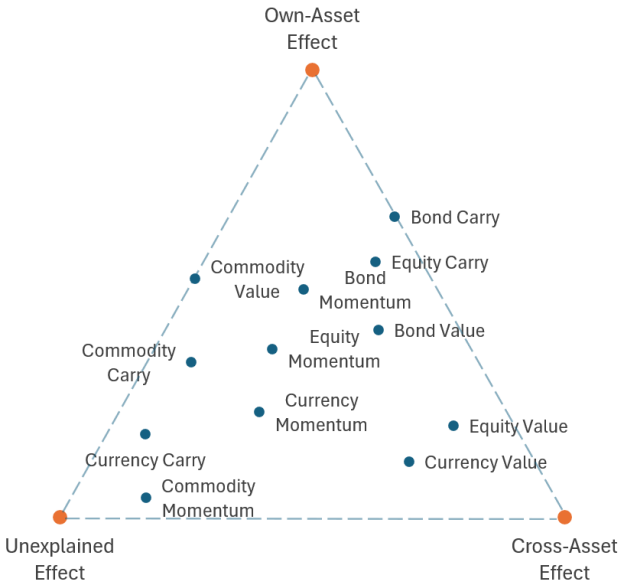
Table 5: Long–Short Pair Portfolio Drivers

	Normalized $\overline{\theta}$ Components			Signal Corr. and Biases		
	$\langle\overline{\text{UE}}\rangle$	$\langle\overline{\text{OA}}\rangle$	$\langle\overline{\text{CA}}\rangle$	ρ_{12}	$\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$	$\frac{\lvert s_i-s_j\rvert}{0.5(s_i+s_j)}$
All Portfolios						
All	0.101	0.803	-0.096	0.353	0.464	0.535
By Asset Class						
Equity	0.072	0.531	-0.397	0.505	0.364	0.368
Bond	0.333	-0.390	0.277	0.588	0.787	0.657
Currency	0.934	-0.008	-0.058	0.569	0.767	0.25
Commodity	0.026	0.934	-0.039	0.258	0.399	0.578
By Signal Type						
Value	-0.456	0.500	0.043	0.495	0.568	0.491
Momentum	0.724	-0.135	-0.140	0.377	0.327	0.386
Carry	0.794	-0.077	-0.129	0.185	0.540	0.767
By Category						
Equity Value	-0.117	-0.205	0.678	0.427	0.289	0.157
Equity Momentum	0.390	-0.376	-0.233	0.810	0.388	0.256
Equity Carry	-0.088	0.571	-0.341	0.243	0.404	0.679
Bond Value	0.160	-0.418	0.423	0.576	1.123	0.807
Bond Momentum	0.263	-0.509	0.228	0.622	0.436	0.563
Bond Carry	0.000	0.672	-0.328	0.562	0.842	0.611
Currency Value	-0.247	-0.123	0.630	0.559	0.309	0.128
Currency Momentum	0.486	0.235	-0.278	0.510	0.314	0.261
Currency Carry	0.737	-0.186	-0.077	0.657	1.821	0.36
Commodity Value	-0.466	0.533	0.001	0.487	0.552	0.545
Commodity Momentum	0.808	-0.043	-0.149	0.245	0.300	0.396
Commodity Carry	0.566	-0.347	0.087	0.054	0.387	0.859

Notes: This table reports, by strategy category, the normalized pair-average unconditional unexplained, own-asset, and cross-asset effects, as well as the within group averages of signal correlation, signal-mean bias, and signal-volatility bias. For each group of pair portfolios, we normalize the group's average component value as a ratio to the sum of the absolute values of the three average components; e.g., $\langle\overline{\text{UE}}\rangle = \overline{\text{UE}}/(|\overline{\text{UE}}|+|\overline{\text{OA}}|+|\overline{\text{CA}}|)$. $\overline{\text{UE}}$, $\overline{\text{OA}}$, and $\overline{\text{CA}}$ are the unconditional unexplained, own-asset, and cross-asset effects corresponding to model equations (8), (9), and (10), respectively; ρ_{ij} is the signal correlation between assets i and j in pair ij; $\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$ measures signal-mean bias, which is the absolute value of the ratio of the mean of a pair's signal difference $(m_i - m_j)$ to the standard deviation of its signal difference s_{ij}; and $\frac{|s_i-s_j|}{0.5(s_i+s_j)}$ measures signal-volatility bias, which is the absolute value of the ratio of the a pair's difference in signal volatilities $(s_i - s_j)$ to the average of their signal volatilities $0.5(s_i + s_j)$. All estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

signal difference is away from being fair (zero). For example, Currency Carry stands out with an average of 1.821, which indicates that the signals of its pairs are on average very

Figure 2: Relative Contribution of Unconditional Unexplained, Own-Asset, and Cross-Asset Effects.



Notes: This figure plots, by strategy category, the absolute values of normalized pair-average unconditional unexplained, own-asset, and cross-asset effects mapped into two dimensions. Sole reliance on just one of $|\overline{\text{UE}}|$, $|\overline{\text{OA}}|$, or $|\overline{\text{CA}}|$ maps to the corners of the triangle. For each group of pair portfolios, we normalize the group's average component value as a ratio to the sum of the absolute values of the three average components; e.g., $\langle\overline{\text{UE}}\rangle = \overline{\text{UE}}/(|\overline{\text{UE}}| + |\overline{\text{OA}}| + |\overline{\text{CA}}|)$. $\overline{\text{UE}}$, $\overline{\text{OA}}$, and $\overline{\text{CA}}$ are the unconditional unexplained, own-asset, and cross-asset effects corresponding to model equations (8), (9), and (10), respectively, estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

biased relative to one another, and are essentially static long–short portfolios. As we noted in Section 2.4.1, signal bias opens the door for the unexplained effect to dominate average return. Indeed, Currency Carry has one of the highest dependencies on the unexplained effect for its performance as can be seen in Figure 2, where it sits close to the bottom left corner (full UE).

We measure signal-volatility bias (cf., Section 2.4.2) as the absolute value of the ratio of the a pair's difference in signal volatilities to the average of their signal volatilities; i.e., $\frac{|s_i - s_j|}{0.5(s_i + s_j)}$. This metric can be interpreted as the relative difference in signal volatilities on a scale of 0 to 2, 0 being no bias and 2 being infinite bias. For example, Commodity Carry stands out with an average signal-volatility bias of 0.859. This corresponds to a ratio of approximately 2.5:1, on average. One of the two signals in an average pair tends to drive the long–short direction for the pair, and its own-asset and cross-asset properties determine returns as discussed in Section 2.4.2 and Section 2.4.3. If this dominating asset has unfavorable OA and CA attributes, then it can dilute the otherwise profitable properties

of its pair asset.

As we noted in Sections 2.4.2, 2.4.3, and 2.4.4, greater signal correlation tends to reduce the potential performance contributions of both OA and CA, and this effect is more direct when signal biases are low. For example, Equity Momentum stands out with an average signal correlation of 0.810—the highest across categories—while having relatively low signal biases. Both its OA and CA components have negative contributions for the average pair strategy in this category. Instead, the average Equity Momentum pair strategy gets its returns mostly from the unexplained effect of asset means rather than its momentum signals. As can be seen in Figure 2, it sits near the center of the triangle because of equal reliance on all three components, i.e., the *absolute values* of the three normalized average component contributions are similar, but that is not a strength when the two signal-driven components (OA and CA) are *negative* contributors before applying the absolute values.

3.5. Predictive Regressions

Our next step is to extend this descriptive analysis to conditional theta (θ), testing its predictive power for pair portfolios. We run cross-sectional Fama and MacBeth (1973) predictive regressions of the pair portfolio return at month $t+1$ on θ at month t. We winsorize the characteristics at the 5% level, but not returns, a typical choice with studies prioritizing raw return variation (Bali et al., 2017).[14] The cross-sectional coefficients, weighted for each month, are averaged across all months to remove any year/month related effects. We report Newey and West (1987) t-statistics, which adjust for heteroskedasticity and autocorrelation. This procedure handles persistent negatively autocorrelated residuals that arise from mean-reversion of the slow-moving characteristic $\overline{\theta}_{ij}$, which has deep overlapping input data that includes lagged returns at every month for several trailing years; see Appendix C.

Table 6 presents the results of four regression models of characteristics over 429 months, with 477,847 observations, and six factor loadings for the most commonly used factors, including Fama and French's (2015) five factors and Carhart's (1997) momentum factor, and asset class and signal type fixed effects where noted. Although these factors are equity-based, some of these exhibit explanatory power for signal-driven pair portfolios, so their inclusion is relevant despite the multiasset nature of our dataset.

[14] Our results are robust to the choice of winsorization and 5% ensures extreme values do not influence our findings.

Column (1) of Table 6 reports θ with coefficient 0.158, which is statistically significant (t-statistic of 3.69), and an Avg. R^2 of 0.154, which magnitude is not atypical for predictive asset pricing tests. However, the relationship of θ to subsequent returns likely varies across asset classes and signals types. Therefore, in Column (2) and the subsequent columns, we add asset class and signal type fixed effects. Fixed effects improve model fit (higher R^2), suggesting they capture important heterogeneity. These controls also reduce θ's coefficient to 0.150, but it remains statistically significant (t-statistic of 3.57).

Column (3) reports the independent predictability of θ's three additive components, replacing θ in the regression and allowing for uneven contributions from each component to be estimated from the data rather than imposed by the theoretical structure. Interestingly, the component that is not a natural part of the sorting-based approach of the benchmark strategy, CA, has a large coefficient of 0.161 which is highly significant (t-statisic of 4.95). OA is not significant while UE is significant at the 5% level. These results suggest that the cross-asset effect matters for pair strategy prediction and that the unexplained effect of asset means, which depends on signal biases, also plays a lesser predictive role; whereas the own-asset effect is surprisingly statistically weak at differentiating pair performance cross-sectionally.

Column (4) reports the coefficient of a CA-only characteristic regression. We find that its coefficient drops in magnitude and significance compared to Column (3), which suggests that CA's predictability depends on multivariate relationships captures by the other two components of θ. This findings supports use of θ for cross-sectional pair prediction, despite CA's central role.

Our predictor, θ, is also economically significant. Table 7 reports the economic impact of each characteristic according to the models in Table 6. At the mean level of θ, its regression coefficient in Column (1) of Table 6 implies an annualized 0.31% mean effect, which is a relative increase of 13.4% in the overall mean pair portfolio annual average return. A one-standard deviation increase in θ translates to a 1.68% pair portfolio average return—a relative increase of 73.5%; and a two-standard deviation increase in θ translates to a 3.35% pair portfolio average return—a relative increase of 147.0%. The remaining models indicate similarly economically significant patterns.

Table 6: Fama-MacBeth Pair Portfolio Predictive Regressions

	(1) θ (No FE)	(2) θ	(3) Components	(4) CA Only
θ	0.158***	0.150***		
	(3.69)	(3.57)		
CA			0.161***	0.056*
			(4.95)	(1.81)
OA			0.080	
			(1.33)	
UE			0.121**	
			(2.42)	
Mkt-RF	-0.004***	-0.005***	-0.004**	-0.006***
	(-2.92)	(-2.89)	(-2.34)	(-3.67)
SMB	-0.005*	-0.004*	-0.004*	-0.005*
	(-1.92)	(-1.74)	(-1.80)	(-1.77)
HML	-0.004	-0.004*	-0.005**	-0.005**
	(-1.44)	(-1.81)	(-2.53)	(-2.08)
RMW	0.002	0.001	0.001	0.001
	(1.11)	(0.98)	(0.55)	(0.59)
CMA	0.001	0.001	0.000	0.001
	(0.44)	(0.29)	(0.08)	(0.54)
UMD	0.004	0.005	0.005	0.008
	(0.81)	(1.02)	(1.13)	(1.31)
Asset Class FE	No	Yes	Yes	Yes
Signal Type FE	No	Yes	Yes	Yes
Avg. Adj. R^2	0.154	0.169	0.180	0.125
N Periods	429	429	429	429
Total Obs.	477,847	477,847	477,847	477,847

Notes: This table reports average coefficients from monthly cross-sectional Fama and MacBeth (1973) regressions of pair portfolio returns at month $t+1$ on factor betas and characteristics at month t, with t-statistics (in parentheses) based on Newey and West (1987) HAC-adjusted standard errors; see Appendix C. Factors are Fama and French's (2015) five factors and Carhart's (1997) momentum factor. θ, UE, OA, and CA are the empirical counterparts to model equations (16), (17), (18), and (19), respectively, which are the model-implied conditional expected return, unexplained effect, own-asset effect, and cross-asset effect given the pair's monthly signal direction, estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Model (1) excludes fixed effects; Models (2), (3), and (4) include fixed effects for asset class and signal type. Constants and fixed effect coefficients are omitted in this report for brevity.

3.6. Selective Base Pairs

In this section, we illustrate the wide applicability of our theoretical and empirical insights. We construct new CS strategies from the bottom up to compare against the benchmark strategy, which includes all base pairs. We use θ_{ij} to be selective about which base

Table 7: Economic Impact of Base Pairs Model Characteristics

Characteristic	Model	Mean Effect	+1 SD Effect	+2 SD Effect
θ	(1)	0.31% [13.4%]	1.68%*** [73.5%]	3.35%*** [147.0%]
θ	(2)	0.29% [12.7%]	1.59%*** [69.8%]	3.18%*** [139.6%]

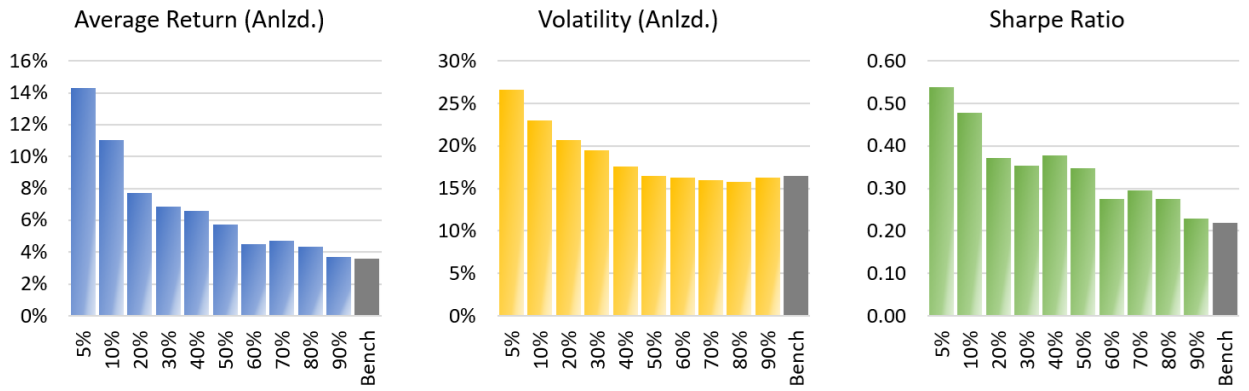
Notes: This table reports the predictability effect of θ on pair portfolio returns according to the coefficient estimates in Table 6. "Mean Effect" reflects the characteristic's mean impact; "+1 SD Effect" and "+2 SD Effect" reflect impacts at one and two standard deviations, respectively. Percentages in brackets are relative to the mean annualized pair portfolio return (2.28%). Significance levels (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$) correspond to the underlying coefficient's t-statistic from Table 6. Model numbers align with Table 6: (1) = θ (No FE), (2) = θ.

pairs ij to include, steering away from "junk" pairs.

We apply our approach to all 12 strategy categories, as well as combinations across strategy categories by asset class, by signal type, and all combined. To balance leverage and volatility contributions of heterogeneous asset classes, we apply standard leverage assumptions based on margin requirements for futures and forwards by asset class in ratio of 5 : 5 : 3 : 1 = Bond Futures : Currency Futures : Equity Futures : Commodity Futures—consistent with Ang et al. (2011). Accordingly, we set leverage multiples for each strategy within an asset class to 4.5 for equities, 7.5 for bonds and currencies, and 1.5 for commodities, resulting in average leverage is 5.25, which is approximately the median leverage of relative value derivative strategies as reported by Ang et al. (2011). This scaling generates approximately 17% volatility across the 12 strategy category benchmark portfolios over the last 20 years, which is comparable to the volatility of the equity market.

We examine 11 selectivity levels for each strategy category, evaluated over the last 20 years of our dataset, October 2003–September 2023, for which we have sufficient signal and return data for all strategies. Each month, we sort base pairs by their θ score and include only the top S% (for different values of S ranging from 5% to 100%). For example, of the total number of base pairs available within a category, if we only include the top 10% by θ, then for each asset class this selectivity level equates to including the top 10 base pairs each month for equity futures; the top seven for bond futures; the top three for currency forwards; and the top 35 for commodity futures. For $S = 100\%$, we include all base pairs, coinciding with the benchmark strategy. Each portfolio's leverage utilization is fixed within a strategy category for uniform comparability across selectivity levels.

Figure 3: Pair-Selective CS Portfolio Performance: Equity Value



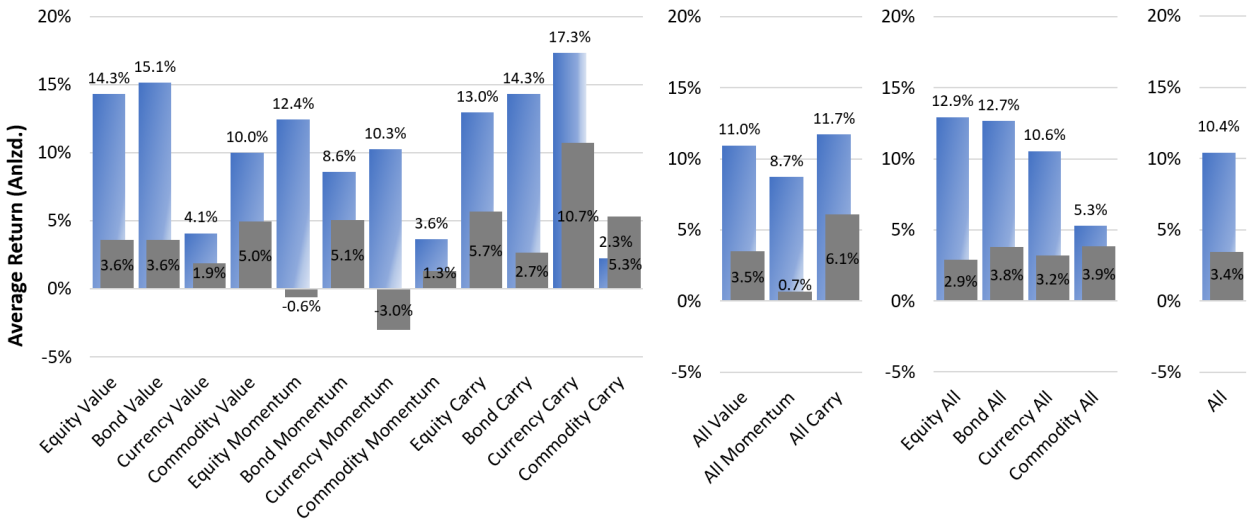
Notes: This figure plots the annualized average return, volatility, and Sharpe ratio for Equity Value based historical simulations over the last 20 years of our sample, October 2003–September 2023, for 11 selectivity levels. Each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies among equity value asset pairs. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities). Leverage multiples for equity portfolios are fixed at 4.5.

Figure 3 illustrates the impact of pair selectivity on annualized average return, volatility, and Sharpe ratio for Equity Value in historical simulations. Selectivity increases moving right to left in each sub-figure. For example, Equity Value's benchmark strategy "Bench" ($S = 100\%$) has an average annualized return of 3.6%. As selectivity increases, performance increases nearly four-fold to 14.3% at the 5% selectivity level. Volatility also rises with more selectivity because of concentration effects. Sharpe ratios, nevertheless, still increase in selectivity despite uniform leverage constraints.

Marked selectivity gains manifest for virtually all strategy categories and group levels in historical simulations. Figure 4 illustrates the impact of pair selectivity on annualized average return over the last 20 years of our sample for each strategy category, asset class, and signal type, as well as overall. Selectivity at the 5% level (blue bars) exhibits an average three-fold increase over the benchmark (100% level, gray bars), exceeding the benchmark in every category with the exception of Commodity Carry.[15] Notably, several momentum strategies,

[15]Recall that Commodity Carry had the lowest R^2 in explanatory panel regressions (Table 3), highest signal-volatility bias among strategy categories (Table 5), and second-highest dependence on the unexplained effect (Table 5), suggesting unmodeled factors influencing this strategy category at the highest selectivity levels. Medium selectivity levels with less concentration effects, nevertheless, exhibit notable gains relative to the benchmark; see Table D.8.

Figure 4: Pair-Selective CS Portfolio Performance: All Strategy Categories



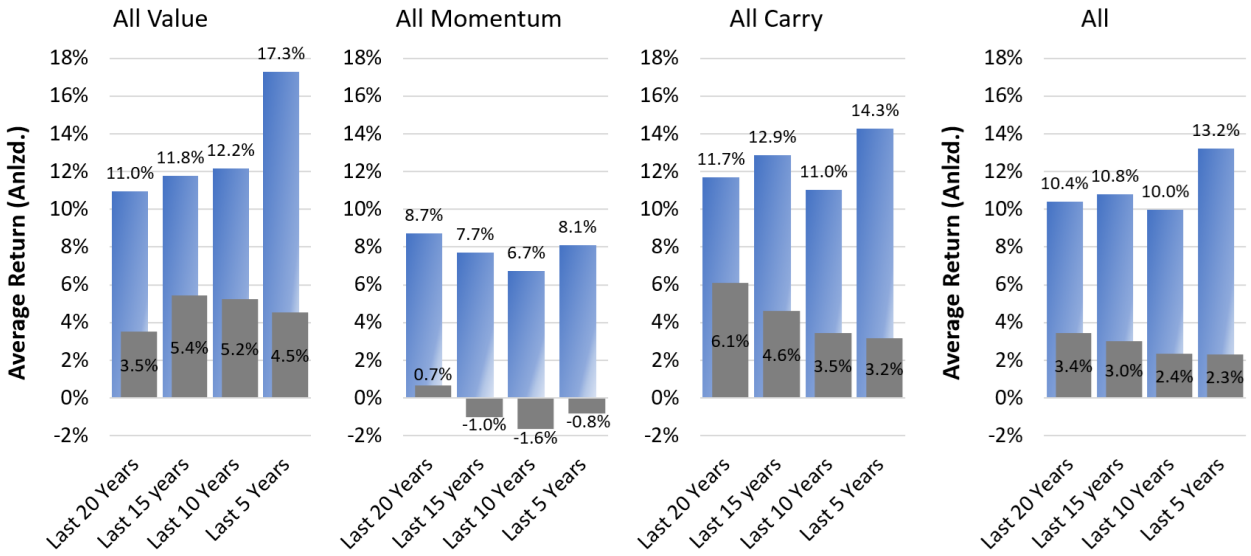
Notes: This figure illustrates the impact of pair selectivity on annualized average pair-selective CS portfolio returns over the last 20 years of our sample, October 2003–September 2023, for each strategy category, asset class, and signal type, as well as overall. For each strategy category, each month, we sort base pairs by their θ score and include only the top $S\%$ of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal types, and all portfolio group portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

which were weak or losing strategies under the benchmark approach, have been converted into strong performers through base pair selectivity. For example, Equity Momentum lost -0.6% under the benchmark approach, but gained 12.4% under the base pairs approach in historical simulations.

Marked selectivity gains also manifest consistently in sub-samples for virtually all strategy categories and group levels in historical simulations. Figure 5 illustrates the impact of pair selectivity on annualized average return over the last 20, 15, 10, and 5 years of our sample for each signal type as well as overall. Selectivity at the 5% level (blue bars) exhibits consistent performance across sub-samples. Selectivity also exhibits consistent outperformance relative to the benchmark strategy (gray bars), which exhibits some evidence of deterioration in later sub-samples.

In Appendix D, Table D.8 reports the average annualized return for 11 selectivity levels for each strategy category, evaluated over the last 20 years of our dataset, October

Figure 5: Pair-Selective CS Portfolio Performance: Sub-Samples



Notes: This figure illustrates the annualized average returns of pair selectivity of pair-selective CS portfolios over the last 20, 15, 10, and 5 years of our sample, October 2003–September 2023, for each signal type and overall. For each strategy category, each month, we sort base pairs by their θ score and include only the top $S\%$ of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Signal type and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

2003–September 2023. Tables D.9, D.10, and D.11 report the corresponding sub-sample performance over the last 15, 10, and 5 years, respectively. For virtually all strategies, more selectivity (i.e., moving right to left in the table) translates to higher average returns per unit of leverage in the historical simulation, and performance is largely consistent in sub-samples. Also in Appendix D, Table D.12 and Table D.13 report the corresponding annualized volatility and Sharpe ratios, respectively, of each strategy corresponding to Table D.8. Volatility also rises with more selectivity because of concentration effects. Sharpe ratios, nevertheless, tend to increase with more selectivity.

3.6.1. Alternative Weighting

Linear rank weighting, as in our benchmark strategy, has been applied in numerous contexts such as under uncertainty (Bertsimas et al., 2010), for stability compared to optimized weights (Kahn and Lemmon, 2013), in factor timing (Bae, 2021), and as a nonparametric

baseline (DeMiguel et al., 2023). Practitioner work supports this. AQR tests linear ranks on factors, with long–short variants showing resilience Asness et al. (2016). Unlike magnitude-based weights Arnott et al. (2005), linear ranking emphasizes ordinal clarity, making it a practical option for long–short strategies across assets.

Many alternatives to the linear-in-signal-rank weighting approach of our benchmark strategy are employed in practice and in the literature.[16] For example, a popular alternative is the Quantile 30 approach (or 30-40-30), which sorts assets each period based on signal strength and goes equally long all assets in the top 30% percent, equally short all assets in the bottom 30%, and neutral in the middle 40% following Fama and French's (1993) factor construction. Another popular alternative is the Fixed N approach to go long the top N assets, short the bottom N, and neutral the middle assets as do Baz et al. (2015). Both of these alternatives attempt to avoid exposure to middle-ranked signals, under the hypothesis that they constitute noise more than signal, and to concentrate exposure equally to higher magnitude signals.

Table 8 reports the average annualized return over the last 20 years of our sample for base pairs selectivity strategies at selectivity levels 5%, 10%, and 30%, and "Linear in Rank," which corresponds to our benchmark strategy. It also reports "Quantile 30" and "Fixed 3" strategy statistics. Quantile 30 exhibits comparable results to our benchmark strategy, with improvements in some categories such as Bond Momentum, Currency Carry, and Commodity Carry, yet underperformance in other categories such as Bond Carry and Currency Value. Fixed 3 likewise exhibits comparable results to our benchmark in most groups, with stronger performance relative to Quantile 30 in a handful of groups. All three signal-sorting CS methods exhibit relatively inconsistent and weaker performance collectively across all groups compared with selective base pairs, except in only a few instances.

Alternative methods could be viewed as filters for undesirable pair characteristics. In our method, we are selecting the most attractive pairs and not doing Quantile 30 or Fixed

[16] Across numerous studies, weighting approaches vary from rank-based Geczy and Samonov (2017), Kroencke et al. (2014), and Harvey et al. (2016) with fixed-N weighting, to signal-scaled Fuertes et al. (2010) and Bianchi et al. (2016), covering all combinations of equity, bond, currency, and commodity futures with value, momentum, and carry signals. Recent works, such as Clare et al. (2021) and Brooks and Moskowitz (2022), refine these strategies with risk adjustments, while Boons and Prado (2019) and Yang and Zhang (2020) extend carry's reach in commodities. This diversity, rooted in top-tier empirical evidence, highlights signal-driven weighting as a cornerstone of modern portfolio design.

Table 8: Base Pairs vs. Signal Sorting Methods: Avg. Return (Anlzd.), Last 20 Years

	Base Pairs			Signal Sorting Methods		
	0.05	0.10	0.30	Linear in Rank	Quantile 30	Fixed 3
All Portfolios:						
All	10.4	8.7	6.9	3.4	3.7	4.1
Asset Class:						
Equity All	12.9	10.7	7.3	2.9	3.3	3.7
Bond All	12.7	10.1	7.1	3.8	4.0	4.0
Currency All	10.6	9.1	6.2	3.2	3.1	3.0
Commodity All	5.3	5.3	7.0	3.9	4.4	5.7
Signal Type:						
All Value	11.0	8.4	7.1	3.5	3.2	6.0
All Momentum	8.7	7.8	5.3	0.7	1.0	0.0
All Carry	11.7	9.9	8.4	6.1	6.9	6.3
Strategy Category:						
Equity Value	14.3	11.0	6.9	3.6	3.9	6.5
Equity Momentum	12.4	8.0	3.8	−0.6	−0.2	−0.8
Equity Carry	13.0	12.7	11.1	5.7	6.3	5.6
Bond Value	15.1	11.5	8.8	3.6	3.8	3.8
Bond Momentum	8.6	6.9	5.4	5.1	6.5	6.5
Bond Carry	14.3	11.9	7.2	2.7	1.6	1.6
Currency Value	4.1	3.0	3.1	1.9	−1.1	2.4
Currency Momentum	10.3	13.5	7.4	−3.0	−3.2	−4.0
Currency Carry	17.3	10.7	8.2	10.7	13.7	10.7
Commodity Value	10.0	8.5	9.5	5.0	6.1	11.5
Commodity Momentum	3.6	3.0	4.4	1.3	1.0	−1.7
Commodity Carry	2.3	4.4	7.2	5.3	6.0	7.2

Notes: This table reports the average annualized return over the last 20 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at selectivity levels 5%, 10%, and 30%, and "Linear in Rank," which corresponds to our benchmark strategy. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Signal type and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios. Quantile 30 sorts assets each period based on signal strength and goes equally long all assets in the top 30% percent, equally short all assets in the bottom 30%, and neutral in the middle 40%. Fixed 3 goes long the top 3 assets, short the bottom 3, and neutral the middle assets.

3 on pair θs. This delivers a natural long–short given each pair strategy is a long–short. These other methods are operating on the individual assets. For example, Fixed 3 in any period consists of the top 3 with the bottom 3 in long–short relationships, with the selection

criteria corresponding to the magnitude of signal differences. While this might correlate with base pairs selection criteria in some cases, base pairs explicitly takes into account the five drivers identified by our theory, providing a lens to assess whether these alternatives provide a "short cut" to desirable pair strategies. Table 8 suggests that such short cuts miss on relevant drivers.

4. Conclusion

This study presents a novel unified framework for analyzing signal-driven cross-sectional (CS) investment strategies by decomposing them into signal-driven base pair strategy portfolios. Grounded in the theoretical insight that any CS strategy with weights linear in signal ranks is the sum of all possible long-short pair portfolios, we develop a model identifying five performance drivers—own-asset predictability, cross-asset predictability, signal correlation, signal mean imbalance, and signal variance imbalance.

Empirically tested across 1,710 pair portfolios, the framework provides robust insights into signal-driven investing. Panel regressions explain 63.7% of long-term average return variation across pair portfolios, with robust cross-asset predictability in Fama-MacBeth regressions. Application to 12 strategy categories across diverse asset classes (equity, bond, currency, and commodity) and signal types (value, momentum, and carry) by pruning ineffective junk pairs and targeting high-potential pair portfolios reveals sweeping performance gains at fixed leverage.

Theoretically, the focus on pair portfolios shifts the lens from aggregate dynamics to inter-asset interactions. The cross-asset effect's prominence challenges approaches that emphasize own-asset effects, while signal imbalances reveal biases that influence performance. This granularity provides new insights into signal-driven strategies, whose alphas traditional models like Fama and French's (2015) five-factor framework struggle to explain fully. Practically, the framework aids portfolio managers in signal selection and risk management, by focusing on top pair portfolios. Robustness to alternative sorting methods, like quantile and fixed-N sorts, underscores its versatility.

Our findings have important implications for asset pricing theory. The prominence of cross-asset effects, contributing substantial return variation, challenges the assumption that returns are primarily driven by own-asset risk factors, as posited by models like Fama and

French (2015). This suggests that inter-asset dependencies play a larger role in signal-driven returns than previously thought. The signal imbalances, such as mean and variance biases, further unlock the picture, capturing the extent to which returns may reflect systematic biases in signal construction rather than risk premia.

These insights open new avenues for asset pricing research. One direction is to explore whether cross-asset effects can be incorporated into multi-factor models, potentially with a new approach that captures inter-asset spillovers. Extending the framework to other signals, such as volatility or quality, or to emerging asset classes, could further test its generality and uncover new pricing anomalies.

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Investment Base Pairs

Internet Appendix

Appendix A Data Details

We use monthly returns and signals obtained from Research Affiliates across 64 futures and forwards markets from four assets classes (equity, bond, currency, and commodity) and three signal types (value, momentum, and carry). Our data for these markets runs through September 2023 with varying start dates (number of observations are listed in Tables A.1, A.2, A.3, and A.4). Our dataset consists of front contracts, which are the most liquid, that are rolled to next nearest contract at the beginning of their expiration month.

Table A.1: Equity Index Futures

	Return (%)			Value			Mom. (×100)			Carry (×100)		
Equity Future	Avg.	SD	N	Avg	SD	N	Avg.	SD	N	Avg.	SD	N
AEX-Index	0.5	6.2	334	-0.1	1.4	294	0.5	2.0	322	0.1	0.5	294
ASX 200	0.4	3.9	280	0.1	1.4	243	0.4	1.2	268	0.2	0.3	243
CAC 40	0.6	5.4	317	0.2	1.3	233	0.6	1.8	305	0.1	0.5	309
DAX	0.6	5.8	394	0.0	1.4	281	0.6	1.8	382	-0.2	0.4	309
Euro Stoxx 50	0.4	5.3	298	0.2	1.3	221	0.3	1.7	286	0.2	0.4	259
FTSE 100	0.4	4.4	465	0.1	1.4	224	0.4	1.2	453	0.1	0.4	309
FTSE MIB	0.4	6.0	232	0.3	1.4	194	0.4	1.9	220	0.2	0.4	194
HANG SENG	0.4	6.2	272	0.2	1.3	309	0.5	1.7	260	0.2	0.7	309
NIKKEI 225	0.2	6.0	420	0.2	1.2	246	0.2	1.8	408	0.1	0.2	290
Nasdaq 100 E-Mini	0.8	6.9	291	0.1	1.3	237	0.7	2.2	279	-0.1	0.1	255
OMX Stockholm 30	0.8	4.8	223	-0.2	1.2	185	0.8	1.5	211	0.2	0.5	185
Russell 2000 E-Mini	0.5	5.5	267	-0.2	1.3	230	0.6	1.6	255	0.0	0.7	230
S&P 500	0.5	4.5	312	0.1	1.4	277	0.5	1.4	300	0.0	0.2	277
Swiss Market Index	0.4	4.0	300	-0.1	1.4	219	0.4	1.4	288	0.2	0.4	297
TSX 60	0.4	3.9	273	0.2	1.3	250	0.5	1.2	261	0.1	0.1	250

Notes: Returns are signals are monthly. Value is the earnings/price ratio (3-year z-score); momentum is the average trailing 12-month return; and carry is the futures roll (spot minus first).

Table A.2: Bond Futures

	Return (%)			Value (×100)			Mom. (×100)			Carry (×100)		
Bond Future	Avg.	SD	N	Avg	SD	N	Avg.	SD	N	Avg.	SD	N
Australia 10Y	0.2	2.3	465	0.3	0.2	308	0.3	0.7	452	0.1	0.1	308
Canada 10Y	0.2	1.8	408	0.2	0.2	308	0.3	0.5	395	0.2	0.2	308
Euro Bobl	0.2	0.9	378	0.1	0.4	308	0.2	0.3	365	0.3	0.2	308
Euro Schatz	0.0	0.4	294	0.1	1.0	307	0.0	0.1	281	0.2	0.3	307
France 10Y	0.2	1.9	137	0.0	0.1	126	0.2	0.6	124	0.3	0.1	126
GB 10Y	0.2	2.2	465	0.1	0.2	308	0.2	0.6	452	0.1	0.2	308
Germany 10Y	0.2	1.6	297	0.1	0.2	308	0.2	0.5	284	0.2	0.1	308
Italy 10Y	0.4	2.7	167	0.2	0.1	157	0.4	0.9	154	0.5	0.2	157
Japan 10Y	0.2	1.4	455	0.1	0.1	308	0.2	0.4	442	0.2	0.1	308
SFE 3Yr	0.0	0.7	264	0.4	0.6	253	0.1	0.2	251	0.1	0.3	253
US 10Y	0.3	1.8	465	0.1	0.2	308	0.3	0.6	452	0.3	0.2	308
US 2Y	0.1	0.5	399	0.0	0.9	308	0.1	0.2	386	0.4	0.5	308
US 5Y	0.2	1.2	424	0.1	0.3	308	0.2	0.4	411	0.4	0.3	308

Notes: Returns are signals are monthly. Value is the real yield; momentum is the average trailing 12-month return; and carry is the excess yield plus term-structure roll.

Table A.3: Currency Forwards

	Return (%)			Value			Mom. (×100)			Carry (×100)		
1M Currency Forward	Avg.	SD	N	Avg	SD	N	Avg.	SD	N	Avg.	SD	N
AUSDollar/USD	0.0	3.4	465	0.1	1.5	305	0.1	1.0	453	0.1	0.2	309
GBPound/USD	-0.2	2.7	417	-0.1	1.4	305	-0.2	0.9	405	0.0	0.1	309
CANDollar/USD	0.0	2.2	417	-0.3	1.5	305	0.0	0.6	405	0.0	0.1	309
Euro/USD	-0.1	2.7	297	0.1	1.4	302	0.0	0.9	285	-0.1	0.1	261
JAPYenUSD	-0.2	3.0	417	-0.2	1.4	305	-0.1	0.9	405	-0.2	0.2	309
NZDollar/USD	0.1	3.3	417	0.2	1.4	305	0.2	1.0	405	0.2	0.2	309
NORKrone/USD	0.0	3.3	417	0.0	1.4	305	0.0	1.0	405	0.1	0.2	309
SWEKrona/USD	0.0	3.2	417	0.0	1.3	305	0.0	1.0	405	0.0	0.1	309
SwissFranc/USD	0.0	3.0	417	0.1	1.4	305	0.1	0.8	405	-0.2	0.1	309

Notes: Returns are signals are monthly. Value is the 5-year real exchange rate reversal (3-year z-score); momentum is the average trailing 12-month return; and carry is the cash rate differential.

Table A.4: Commodity Futures

	Return (%)			Value			Mom. (×100)			Carry (×100)		
Commodity Future	Avg.	SD	N	Avg	SD	N	Avg.	SD	N	Avg.	SD	N
Aluminum	-0.1	5.7	314	-0.2	0.4	249	0.0	1.9	302	-0.3	0.4	277
Blendstock Gasoline	1.4	10.2	465	-0.4	0.7	309	1.3	2.9	453	0.4	3.6	309
Cocoa	-0.1	7.9	465	-0.2	0.4	309	-0.2	2.0	453	-0.2	0.8	309
Coffee	-0.1	10.3	465	-0.2	0.6	309	-0.1	3.3	453	-0.8	0.8	309
Copper	0.9	7.6	453	-0.5	1.1	309	0.9	2.6	441	-0.1	0.5	309
Corn	-0.2	7.4	465	-0.2	0.6	309	-0.2	2.1	453	-0.7	1.7	309
Cotton	0.3	7.4	465	-0.1	0.4	309	0.3	2.5	453	-0.5	1.4	309
Crude Oil, Brent	1.0	9.2	410	-0.5	0.8	309	0.9	3.1	398	0.0	1.4	309
Feeder Cattle	0.2	4.1	465	-0.2	0.3	309	0.2	1.2	453	-0.3	1.1	309
Gold	0.2	4.4	465	-0.5	0.6	309	0.2	1.2	453	-0.2	0.2	309
Heating Oil	0.9	9.3	465	-0.5	0.8	309	0.8	3.1	453	-0.1	1.9	309
Kansas Wheat	0.0	7.5	465	-0.2	0.5	309	0.1	2.2	453	-0.7	0.8	309
Lead	0.9	8.2	274	-0.7	1.4	209	0.9	2.7	262	0.0	0.5	273
Lean Hogs	-0.2	7.2	465	-0.1	0.3	309	-0.2	2.2	453	-0.7	5.0	309
Live Cattle	0.2	3.9	465	-0.2	0.2	309	0.2	1.1	453	-0.3	1.7	309
Low Sulphur Gasoil	1.0	9.2	447	-0.5	0.8	309	0.9	3.1	435	0.0	1.5	309
Natural Gas	-0.7	14.3	401	-0.3	0.8	309	-0.5	4.5	389	-2.1	4.6	309
Nickel	0.8	10.1	314	-0.6	1.3	249	1.0	3.4	302	0.1	0.5	277
Platinum	0.4	6.4	465	-0.3	0.6	309	0.4	1.8	453	0.0	0.3	309
Silver	0.3	8.0	465	-0.5	0.8	309	0.3	2.1	453	-0.2	0.1	309
Soybean Meal	0.8	7.2	465	-0.2	0.4	309	0.8	1.8	453	0.3	1.3	309
Soybean Oil	0.1	7.2	465	-0.2	0.6	309	0.1	2.2	453	-0.4	0.8	309
Soybeans	0.4	6.4	465	-0.2	0.5	309	0.4	1.8	453	-0.1	1.2	309
Sugar	0.6	9.4	465	-0.2	0.6	309	0.6	2.6	453	0.1	2.0	309
WTI Crude	0.8	10.4	465	-0.4	0.7	309	0.8	3.2	453	-0.4	2.1	309
Wheat	-0.3	7.6	465	-0.2	0.5	309	-0.2	2.1	453	-1.1	0.7	309
Zinc	0.2	7.6	314	-0.5	0.9	249	0.3	2.7	302	-0.2	0.4	277

Notes: Returns are signals are monthly. Value is the 5-year price reversal; momentum is the average trailing 12-month return; and carry is the futures roll (first minus second).

Appendix B Proofs

Proof of Theorem 1. We provide a sketch of the proof. Consider the highest-ranked signal, $x_{[1]}$, which stands in a long position in all pair strategies with the remaining $n-1$ assets. This observation accounts for $n-1$ pair strategies, a gross asset weight of positive $n-1$ units on asset [1] in the benchmark n-asset CS strategy, and a gross asset weight of negative 1 unit on assets [2] through [n]. Next, consider the second-highest-ranked signal, $x_{[2]}$, which stands in a long position in all pair strategies with the remaining lower-signal-ranked $n-2$ assets. This observation accounts for $n-2$ additional pair strategies, an additional gross asset weight of $n-2$ units on asset [2] in the benchmark strategy—$n-3$ units net of its role in the pair with asset [1], and an additional gross asset weight of negative 1 unit on assets [3] through [n]. Continuing in this manner until the lowest-ranked asset, counting pair strategies represented, collecting gross asset weights, and normalizing to scaled weights yields the result. □

Proof of Theorem 2. Recall from (2) that the pair strategy return for arbitrary assets i and j is $r_{ij} = \text{sign}(x_i - x_j) \cdot (r_i - r_j)$. To compute its expected value, we apply the law of total expectation, conditioning on the ordering of the signals:

$$\mathbf{E}[r_{ij}] = \mathbf{E}[r_{ij}|x_i > x_j] \cdot \mathbf{P}[x_i > x_j] + \mathbf{E}[r_{ij}|x_i < x_j] \cdot \mathbf{P}[x_i < x_j]. \tag{B1}$$

We begin by evaluating the conditional expectation in the case $x_i > x_j$, in which $\text{sign}(x_i - x_j) = 1$ so that $r_{ij} = r_i - r_j$. Under the model of (4) and (5), this difference in asset returns is $r_i - r_j = (\mu_i - \mu_j) + (b_{ii} - b_{ij})x_i + (b_{ji} - b_{jj})x_j + (\varepsilon_i - \varepsilon_j)$, which yields:

$$\mathbf{E}[r_{ij}|x_i > x_j] = (\mu_i - \mu_j) + (b_{ii} - b_{ij})\mathbf{E}[x_i|x_i > x_j] + (b_{ji} - b_{jj})\mathbf{E}[x_j|x_i > x_j], \tag{B2}$$

where we have applied the independence signals and noise terms ε_i and ε_j and the zero means of the noise terms.

To resolve the right-hand side of (B2), we evaluate the conditional expectations $\mathbf{E}[x_i|x_i > x_j]$ and $\mathbf{E}[x_j|x_i > x_j]$ in (B2). Recall that signals x_i and x_j are jointly normal random variables with correlation ρ_{ij} and each signal has marginal distribution $x_k \sim \mathcal{N}(m_k, s_k)$ for $k = i, j$. The distribution of each x_k is equivalent to $m_k + s_k z_k$, where $z_k \sim \mathcal{N}(0,1)$ is the z-score of signal x_k and $\mathbf{Corr}[z_i, z_j] = \rho_{ij}$. Also recall that $y_{ij} = -\frac{m_i - m_j}{s_{ij}}$ and $s_{ij} = \mathbf{SD}[x_i - x_j] = \sqrt{s_i^2 + s_j^2 - 2s_i s_j \rho_{ij}}$ are the z-score at zero and the standard deviation, respectively, of the signal gap, $x_i - x_j$. Let w_{ij} be the z-score of the signal gap, $w_{ij} = \frac{x_i - x_j - (m_1 - m_2)}{s_{ij}}$. Note

that $w_{ij} = \frac{s_i z_i - s_j z_j}{s_{ij}}$ and $w_{ij} \sim \mathcal{N}(0,1)$. The correlations of each z_k with w are given by:

$$\rho_{i:ij} = \mathbf{Corr}[z_i, w] = \mathbf{Corr}\left[z_i, \frac{s_i z_i - s_j z_j}{s_{ij}}\right] = \frac{s_i - s_j \rho_{ij}}{s_{ij}}, \tag{B3}$$

$$\rho_{j:ij} = \mathbf{Corr}[z_j, w] = \mathbf{Corr}\left[z_j, \frac{s_i z_i - s_j z_j}{s_{ij}}\right] = \frac{s_i \rho_{ij} - s_j}{s_{ij}}. \tag{B4}$$

Therefore, the conditional expected value of signal x_k given $x_i > x_j$ satisfies

$$\mathbf{E}[x_k | x_i > x_j] = \mathbf{E}[m_k + s_k z_k | w_{ij} > y_{ij}] = m_k + s_k \mathbf{E}[z_k | w_{ij} > y_{ij}]. \tag{B5}$$

Applying Lemma 4 twice, with $u_1 = z_k$, $u_2 = w_{ij}$, $u = y_{ij}$, and $\eta = \rho_{k;ij}$ for each of $k = i, j$, we have $\mathbf{E}[z_i | w_{ij} > y_{ij}] = \rho_{i:ij}\phi(y_{ij})/\Phi(-y_{ij})$ and $\mathbf{E}[z_j | w_{ij} > y_{ij}] = \rho_{j:ij}\phi(y_{ij})/\Phi(-y_{ij})$.

Substitution of these last two expressions into (B5) for $k = i, j$ and the resultant expressions of (B5) into (B2), yields:

$$\begin{aligned}\mathbf{E}[r_{ij} | x_i > x_j] = (\mu_i - \mu_j) + (b_{ii} - b_{ij}) \left(m_i + s_i \rho_{i:ij} \frac{\phi(y_{ij})}{\Phi(-y_{ij})}\right) \\ + (b_{ji} - b_{jj}) \left(m_j + s_j \frac{\rho_{j:ij}\phi(y_{ij})}{\Phi(-y_{ij})}\right),\end{aligned} \tag{B6}$$

which can be written more compactly as

$$\mathbf{E}[r_{ij} | x_i > x_j] = \mu_i - \mu_j + \sum_{k=i,j} (b_{ki} - b_{kj}) \left(m_k + s_k \rho_{k:ij} \frac{\phi(y_{ij})}{\Phi(-y_{ij})}\right). \tag{B7}$$

To obtain the conditional expectation of the strategy return in the symmetric case of $x_i < x_j$, swap i and j in (B6), use the identities $r_{ij} = r_{ji}$, $y_{ji} = -y_{ij}$, $s_{ij} = s_{ji}$, and $\rho_{k:ji} = -\rho_{k,ij}$, and the fact that normal pdf is symmetric around zero, $\phi(-u) = \phi(u)$, and write compactly:

$$\mathbf{E}[r_{ij} | x_i < x_j] = -\left[\mu_i - \mu_j + \sum_{k=i,j} (b_{ki} - b_{kj}) \left(m_k - s_k \rho_{k:ij} \frac{\phi(y_{ij})}{\Phi(y_{ij})}\right)\right]. \tag{B8}$$

To resolve the right-hand side of (B1), we now obtain the conditional probabilities in (B1): $\mathbf{P}[x_i > x_j] = \mathbf{P}[w_{ij} > y_{ij}] = 1 - \Phi(y_{ij}) = \Phi(-y_{ij})$, where we have applied the symmetry of the standard normal cdf, and $\mathbf{P}[x_i < x_j] = \mathbf{P}[w_{ij} < y_{ij}] = \Phi(y_{ij})$. To complete the proof, we substitute these conditional probabilities together with (B7) and (B8) into (B1) and use the symmetry of the standard normal cdf, $\Phi(-u) - \Phi(u) = 1 - 2\Phi(u)$, to simplify and obtain:

$$\mathbf{E}[r_{ij}] = (\mu_i - \mu_j)[1 - 2\Phi(y_{ij})] + \sum_{k=i,j} (b_{ki} - b_{kj}) \left[m_k(1 - 2\Phi(y_{ij})) + 2 s_k \rho_{k:ij} \phi(y_{ij})\right],$$

which coincides with (6)and completes the proof. □

Proof of Theorem 3. See the derivation of (15) in the proof of Theorem 2; cf. (B7). The derivation of the symmetric conditional expectation, $\mathbf{E}[r_{ij} | x_i < x_j]$, is also in the proof of

Theorem 2, where it is expressed in (B8). □

Lemma 4. *Let u_1 and u_2 be bivariate standard normal random variables (mean zero, variance one) with covariance η. Then, $\mathbf{E}[u_1|u_2 < u] = -\eta\phi(u)/\Phi(u)$ and $\mathbf{E}[u_1|u_2 > u] = \eta\phi(u)/\Phi(-u)$, where $\phi(u)$ and $\Phi(u)$ are the pdf and cdf, respectively, of a standard normal random variable.*

Proof of Lemma 4. These standard results follow from the fact that the conditional distribution of u_1 given u_2 is normal and from expected value calculations for truncated bivariate normal random variables. See, for example, Maddala (1983), p. 367. □

Appendix C Heteroskedasticity and Autocorrelation Consistent Standard Errors

For the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance applied to our explanatory contemporaneous panel regressions, we select lag lengths to match the overlap of data used in the rolling window estimates of our characteristics and to match the longest lag length in pooled regressions of characteristics with different overlap windows. Hodrick (1992) notes long-memory in overlapping return contexts such as ours, "warranting lags up to the overlap horizon" (p. 362). Autocorrelated residuals arise from long-memory mean reversion in the slow-moving characteristic $\overline{\theta}_{ij}$, which is a nonlinear function of deep overlapping data including lagged returns at every month for several trailing years. Matching data overlap is conservative.

For the Newey and West (1987) HAC covariance estimator applied to our Fama and MacBeth (1973) predictive regression coefficients, we select a lag length that adheres to the econometric guideline that when dealing with deep overlapping data in characteristics, the maximum lag length should approximate $T/3$, a widely accepted threshold for ensuring robust variance estimation in the presence of significant autocorrelation Greene (2003); Hamilton (1994); Hayashi (2000). Newey and West (1987) suggest $L = O(T^{1/4})$, but practical extensions to $T/3$ are endorsed for persistent dependence, as Stock and Watson (2011) note: "lags up to $T/3$ or $T/4$ are common when autocorrelation is strong" (p. 583). Similarly, Wooldridge (2013) advocates $L \approx T/3$ "to achieve consistency in time series with serial correlation" (p. 426), and Lutkepohl (2005) supports this for "long-memory processes" (p. 152). We align with this guidance, justified by the complex autocorrelation structure induced by our data.

Contrary to popular intuition that longer lags always inflate standard errors by adding noise, our SEs decrease and stabilize with increasing lags. Overlapping data, as in our context, introduces mean reversion, as Hansen and Hodrick (1980) note: "longer lags are

required to correct for negative serial correlation in overlapping regressions" (p. 840), a view echoed by Jegadeesh (1991) who finds "SEs decrease with lags matching overlap length due to mean-reverting errors" (p. 78). Hamilton (1994)'s advises to extend lags "to where autocorrelations diminish" (p. 281) and this reduction is driven in our data by a cumulative weighted autocorrelation function (ACF) that drops below -0.6 and sustains negativity before stabilizing around $T/3$, reflecting significant negative terms (e.g., -0.11813 at lag 3, -0.1161 at lag 27, -0.10529 at lag 121), with $T/3$ fully accounting for this effect while remaining aligned with theoretical bounds. These results are reinforced by Stock and Watson (2011), who note "negative autocorrelation can halve SEs with sufficient lags" (p. 584); by Cochrane (2005), who advises that "with overlapping data, longer lags often decrease SEs by accounting for negative autocorrelation from mean reversion" (p. 186); and by Hayashi (2000), who explains that "negative autocorrelations, when weighted, can substantially reduce the HAC variance" (p. 413), amplified here by overlapping data reducing effective sample independence (up to 56% overlap, 240/429). Extending beyond $T/3$ yields negligible impact ($\approx$0.6%), risking noise inclusion, whereas shorter lags miss part of the stabilization, underestimating the SE adjustment.

Appendix D Additional Statistics

Table D.1: Percentiles and Statistics for Model Unconditional Expected Return $\overline{\theta}$ of Long–Short Pair Portfolios

	$\overline{\theta}$ Percentiles (%)					Avg. (%)	SD (%)
	Min	25	50	75	Max	$\overline{\theta}$	$\overline{\theta}$
All Portfolios							
All	-21.71	-0.17	0.10	0.52	24.19	0.16	0.884
By Asset Class							
Equity	-20.47	-0.16	0.06	0.30	9.14	0.06	0.619
Bond	-10.09	-0.07	0.01	0.10	10.30	0.03	0.354
Currency	-8.42	-0.05	0.06	0.21	2.76	0.11	0.325
Commodity	-21.71	-0.27	0.21	0.71	24.19	0.21	1.020
By Signal Type							
Value	-21.71	-0.21	0.07	0.46	24.19	0.11	1.063
Momentum	-20.47	-0.14	0.11	0.54	16.17	0.18	0.779
Carry	-13.07	-0.19	0.12	0.55	10.30	0.18	0.818
By Category							
Equity Value	-3.53	-0.05	0.11	0.31	6.28	0.13	0.439
Equity Momentum	-20.47	-0.31	-0.09	0.13	9.14	-0.11	0.687
Equity Carry	-13.07	-0.05	0.17	0.43	4.47	0.19	0.638
Bond Value	-10.09	-0.09	0.00	0.08	4.35	0.04	0.444
Bond Momentum	-2.02	-0.07	0.02	0.09	2.19	-0.01	0.201
Bond Carry	-4.50	-0.06	0.03	0.13	10.30	0.07	0.381
Currency Value	-1.26	-0.10	-0.01	0.13	2.47	0.04	0.281
Currency Momentum	-1.38	-0.06	0.04	0.17	2.49	0.11	0.328
Currency Carry	-8.42	0.03	0.17	0.30	2.76	0.16	0.348
Commodity Value	-21.71	-0.40	0.15	0.65	24.19	0.13	1.275
Commodity Momentum	-12.40	-0.14	0.28	0.71	16.17	0.27	0.858
Commodity Carry	-6.78	-0.36	0.16	0.78	5.02	0.20	0.938

Notes: This table reports percentiles and statistics for $\overline{\theta}$, which is the unconditional expected return corresponding to model equation (7). Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.2: Percentiles and Statistics for Model Unconditional Unexplained Effect $\overline{\text{UE}}$ of Long–Short Pair Portfolios

	$\overline{\text{UE}}$ Percentiles (%)					Avg. (%)	SD (%)
	Min	25	50	75	Max	$\overline{\text{UE}}$	$\overline{\text{UE}}$
All Portfolios							
All	-54.44	-0.03	0.03	0.22	36.10	0.020	1.414
By Asset Class							
Equity	-9.73	-0.05	0.00	0.09	23.29	0.021	0.499
Bond	-12.65	-0.02	0.02	0.12	16.03	0.047	0.727
Currency	-11.90	-0.00	0.02	0.09	23.40	0.113	0.829
Commodity	-54.44	-0.04	0.05	0.29	36.10	0.006	1.661
By Signal Type							
Value	-54.44	-0.64	-0.08	0.02	23.29	-0.581	1.991
Momentum	-8.34	0.02	0.10	0.30	36.10	0.294	0.810
Carry	-15.75	-0.02	0.05	0.33	33.77	0.246	1.160
By Category							
Equity Value	-9.73	-0.08	-0.01	0.02	23.29	-0.043	0.588
Equity Momentum	-8.34	0.01	0.08	0.27	11.99	0.199	0.492
Equity Carry	-3.45	-0.16	-0.02	0.02	1.47	-0.115	0.333
Bond Value	-12.65	-0.13	0.00	0.18	9.48	0.034	0.829
Bond Momentum	-1.00	0.01	0.05	0.12	1.77	0.099	0.163
Bond Carry	-9.89	-0.04	0.01	0.08	16.03	0.000	0.964
Currency Value	-11.90	-0.01	0.00	0.04	2.24	-0.036	0.487
Currency Momentum	-3.19	0.00	0.03	0.08	7.28	0.124	0.413
Currency Carry	-11.85	-0.07	0.05	0.42	23.40	0.250	1.330
Commodity Value	-54.44	-1.10	-0.29	-0.00	22.30	-0.876	2.353
Commodity Momentum	-6.02	0.02	0.13	0.37	36.10	0.358	0.929
Commodity Carry	-15.75	0.00	0.12	0.49	33.77	0.375	1.269

Notes: This table reports percentiles and statistics for $\overline{\text{UE}}$, which is the unconditional unexplained effect corresponding to model equation (8). Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.3: Percentiles and Statistics for Model Unconditional Own-Asset Effect $\overline{\text{OA}}$ of Long–Short Pair Portfolios

	$\overline{\text{OA}}$ Percentiles (%)					Avg. (%)	SD (%)
	Min	25	50	75	Max	$\overline{\text{OA}}$	$\overline{\text{OA}}$
All Portfolios:							
All	-32.78	-0.31	0.07	0.51	40.53	0.159	1.689
Asset Class:							
Equity	-21.24	-0.36	0.05	0.61	30.97	0.155	1.386
Bond	-29.07	-0.19	0.01	0.20	27.80	-0.055	1.304
Currency	-31.76	-0.17	-0.01	0.18	14.06	-0.001	0.812
Commodity	-32.78	-0.34	0.12	0.58	40.53	0.213	1.859
Signal Type:							
Value	-32.05	-0.18	0.21	0.89	40.53	0.637	2.468
Momentum	-32.78	-0.31	0.01	0.36	29.04	-0.055	1.079
Carry	-31.76	-0.42	0.04	0.49	30.97	-0.024	1.261
Strategy Category:							
Equity Value	-8.25	-0.38	-0.10	0.14	10.77	-0.075	0.724
Equity Momentum	-21.24	-0.67	-0.21	0.25	26.57	-0.192	1.725
Equity Carry	-5.96	0.19	0.64	1.11	30.97	0.743	1.228
Bond Value	-29.07	-0.31	0.05	0.36	27.80	-0.089	1.919
Bond Momentum	-4.19	-0.25	-0.10	-0.01	3.11	-0.192	0.436
Bond Carry	-23.03	0.01	0.11	0.33	4.55	0.135	1.168
Currency Value	-5.11	-0.21	-0.11	-0.02	7.83	-0.018	0.595
Currency Momentum	-5.29	-0.04	0.07	0.20	8.64	0.060	0.356
Currency Carry	-31.76	-0.38	0.05	0.33	14.06	-0.063	1.283
Commodity Value	-32.05	-0.02	0.50	1.22	40.53	1.003	2.832
Commodity Momentum	-32.78	-0.29	0.09	0.45	29.04	-0.019	1.029
Commodity Carry	-17.05	-0.60	-0.14	0.32	9.95	-0.230	1.208

Notes: This table reports percentiles and statistics for $\overline{\text{OA}}$, which is the unconditional own-asset effect corresponding to model equation (9). Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.4: Percentiles and Statistics for Model Unconditional Cross-Asset Effect $\overline{\text{CA}}$ of Long–Short Pair Portfolios

	$\overline{\text{CA}}$ Percentiles (%)					Avg. (%)	SD (%)
	Min	25	50	75	Max	$\overline{\text{CA}}$	$\overline{\text{CA}}$
All Portfolios:							
All	-42.76	-0.34	-0.01	0.33	32.06	-0.019	1.738
Asset Class:							
Equity	-42.76	-0.47	-0.02	0.32	16.15	-0.116	1.408
Bond	-28.47	-0.20	-0.02	0.13	31.36	0.039	1.289
Currency	-16.95	-0.14	-0.01	0.15	21.05	-0.007	0.820
Commodity	-35.47	-0.37	-0.01	0.40	32.06	-0.009	1.926
Signal Type:							
Value	-35.47	-0.23	0.14	0.65	32.06	0.055	2.606
Momentum	-29.05	-0.30	-0.05	0.19	29.52	-0.057	0.968
Carry	-42.76	-0.49	-0.08	0.31	26.84	-0.040	1.438
Strategy Category:							
Equity Value	-31.94	0.01	0.24	0.55	8.80	0.248	0.915
Equity Momentum	-27.43	-0.48	-0.06	0.28	16.15	-0.119	1.629
Equity Carry	-42.76	-0.75	-0.33	0.04	7.64	-0.443	1.437
Bond Value	-28.47	-0.34	-0.05	0.33	31.36	0.090	1.847
Bond Momentum	-2.81	-0.05	0.03	0.14	3.58	0.086	0.387
Bond Carry	-13.19	-0.30	-0.10	0.02	23.62	-0.066	1.266
Currency Value	-8.24	0.02	0.11	0.21	6.68	0.092	0.536
Currency Momentum	-8.49	-0.14	-0.07	0.01	3.76	-0.071	0.343
Currency Carry	-16.95	-0.34	-0.04	0.28	21.05	-0.026	1.329
Commodity Value	-35.47	-0.33	0.17	0.85	32.06	0.002	3.074
Commodity Momentum	-29.05	-0.33	-0.07	0.22	29.52	-0.066	0.897
Commodity Carry	-17.86	-0.47	-0.02	0.43	26.84	0.058	1.461

Notes: This table reports percentiles and statistics for $\overline{\text{CA}}$, which is the unconditional cross-asset effect corresponding to model equation (10). Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.5: Percentiles and Statistics for Signal Correlation of Long–Short Pair Portfolios

	ρ_{12} Percentiles					Average	Std. Dev.
	Min	25	50	75	Max	ρ_{12}	ρ_{12}
All Portfolios:							
All	-0.92	0.08	0.36	0.67	1.00	0.353	0.375
Asset Class:							
Equity All	-0.88	0.24	0.57	0.81	1.00	0.505	0.346
Bond All	-0.86	0.46	0.66	0.80	0.99	0.588	0.312
Currency All	-0.87	0.38	0.66	0.81	0.99	0.569	0.306
Commodity All	-0.92	0.01	0.24	0.52	1.00	0.258	0.360
Signal Type:							
All Value	-0.89	0.30	0.58	0.77	1.00	0.495	0.366
All Momentum	-0.92	0.13	0.37	0.68	1.00	0.377	0.363
All Carry	-0.87	-0.04	0.12	0.40	0.99	0.185	0.333
Strategy Category:							
Equity Value	-0.88	0.26	0.47	0.65	0.96	0.427	0.292
Equity Momentum	-0.66	0.75	0.85	0.91	1.00	0.810	0.155
Equity Carry	-0.74	0.04	0.21	0.44	0.99	0.243	0.284
Bond Value	-0.86	0.41	0.70	0.86	0.99	0.576	0.374
Bond Momentum	-0.71	0.51	0.68	0.80	0.99	0.622	0.269
Bond Carry	-0.74	0.44	0.62	0.76	0.99	0.562	0.283
Currency Value	-0.81	0.38	0.68	0.81	0.99	0.559	0.339
Currency Momentum	-0.53	0.31	0.56	0.76	0.99	0.510	0.300
Currency Carry	-0.87	0.54	0.73	0.84	0.99	0.657	0.255
Commodity Value	-0.89	0.30	0.58	0.76	1.00	0.487	0.378
Commodity Momentum	-0.92	0.05	0.26	0.44	0.99	0.245	0.319
Commodity Carry	-0.86	-0.09	0.04	0.18	0.95	0.054	0.248

Notes: This table reports percentiles and statistics for ρ_{ij}, which is the correlation of a pair's signals. Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.6: Percentiles and Statistics for Signal-Mean Bias of Long–Short Pair Portfolios

	$\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$ Percentiles					Average	Std. Dev.
	Min	25	50	75	Max	$\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$	$\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$
All Portfolios:							
All	0.00	0.14	0.32	0.57	15.96	0.464	0.570
Asset Class:							
Equity All	0.00	0.12	0.27	0.50	4.57	0.364	0.360
Bond All	0.00	0.29	0.55	0.97	10.60	0.787	0.874
Currency All	0.00	0.13	0.31	0.91	15.96	0.767	1.186
Commodity All	0.00	0.14	0.30	0.52	8.12	0.399	0.384
Signal Type:							
All Value	0.00	0.18	0.41	0.76	10.60	0.568	0.624
All Momentum	0.00	0.13	0.27	0.44	7.66	0.327	0.293
All Carry	0.00	0.14	0.32	0.66	15.96	0.540	0.727
Strategy Category:							
Equity Value	0.00	0.11	0.23	0.39	2.56	0.289	0.259
Equity Momentum	0.00	0.15	0.32	0.53	4.57	0.388	0.344
Equity Carry	0.00	0.11	0.27	0.57	3.93	0.404	0.437
Bond Value	0.00	0.37	0.76	1.48	10.60	1.123	1.216
Bond Momentum	0.00	0.20	0.39	0.62	3.27	0.436	0.314
Bond Carry	0.00	0.36	0.68	1.09	8.53	0.842	0.734
Currency Value	0.00	0.08	0.21	0.38	5.24	0.309	0.411
Currency Momentum	0.00	0.10	0.21	0.36	7.66	0.314	0.472
Currency Carry	0.00	0.73	1.52	2.20	15.96	1.821	1.616
Commodity Value	0.00	0.22	0.45	0.78	8.12	0.552	0.441
Commodity Momentum	0.00	0.12	0.25	0.41	2.92	0.300	0.247
Commodity Carry	0.00	0.12	0.26	0.49	5.72	0.387	0.428

Notes: This table reports percentiles and statistics for $\left\lvert\frac{m_i-m_j}{s_{ij}}\right\rvert$, which measures signal-mean bias as the absolute value of the ratio of the mean of a pair's signal difference $(m_i - m_j)$ to the standard deviation of its signal difference s_{ij}. Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.7: Percentiles and Statistics for Signal-Volatility Bias of Long–Short Pair Portfolios

	$\frac{\lvert s_i - s_j \rvert}{0.5(s_i+s_j)}$ Percentiles					Average	Std. Dev.
	Min	25	50	75	Max	$\frac{\lvert s_i - s_j \rvert}{0.5(s_i+s_j)}$	$\frac{\lvert s_i - s_j \rvert}{0.5(s_i+s_j)}$
All Portfolios:							
All	0.00	0.18	0.43	0.80	1.93	0.535	0.430
Asset Class:							
Equity All	0.00	0.09	0.23	0.52	1.93	0.368	0.376
Bond All	0.00	0.31	0.59	0.97	1.83	0.657	0.425
Currency All	0.00	0.06	0.16	0.35	1.67	0.250	0.254
Commodity All	0.00	0.23	0.48	0.85	1.93	0.578	0.434
Signal Type:							
All Value	0.00	0.14	0.39	0.76	1.83	0.491	0.409
All Momentum	0.00	0.15	0.33	0.55	1.67	0.386	0.294
All Carry	0.00	0.35	0.71	1.14	1.93	0.767	0.495
Strategy Category:							
Equity Value	0.00	0.05	0.10	0.19	1.69	0.157	0.186
Equity Momentum	0.00	0.10	0.21	0.36	1.61	0.256	0.211
Equity Carry	0.00	0.31	0.62	1.03	1.93	0.679	0.440
Bond Value	0.00	0.41	0.78	1.19	1.83	0.807	0.475
Bond Momentum	0.00	0.25	0.51	0.84	1.59	0.563	0.370
Bond Carry	0.00	0.31	0.54	0.89	1.67	0.611	0.388
Currency Value	0.00	0.03	0.07	0.14	1.35	0.128	0.179
Currency Momentum	0.00	0.08	0.19	0.36	1.67	0.261	0.241
Currency Carry	0.00	0.15	0.30	0.51	1.60	0.360	0.282
Commodity Value	0.00	0.23	0.49	0.80	1.73	0.545	0.373
Commodity Momentum	0.00	0.16	0.36	0.56	1.45	0.396	0.282
Commodity Carry	0.00	0.42	0.85	1.26	1.93	0.859	0.509

Notes: This table reports percentiles and statistics for $\frac{\lvert s_i - s_j \rvert}{0.5(s_i+s_j)}$, which measures signal-volatility bias as the absolute value of the ratio of the a pair's difference in signal volatilities $(s_i - s_j)$ to the average of their signal volatilities $0.5(s_i + s_j)$. Estimates are over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities).

Table D.8: Combined Performance: Average Return (Anlzd.), Last 20 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
All Portfolios:											
All	10.4	8.7	7.4	6.9	6.3	5.9	5.3	4.9	4.7	4.2	3.4
Asset Class:											
Equity All	12.9	10.7	7.4	7.3	6.8	6.0	5.3	4.9	4.3	3.7	2.9
Bond All	12.7	10.1	8.8	7.1	6.5	6.2	5.6	5.3	5.1	4.4	3.8
Currency All	10.6	9.1	6.7	6.2	5.0	4.7	4.1	3.7	4.2	3.7	3.2
Commodity All	5.3	5.3	6.6	7.0	6.8	6.5	6.1	5.9	5.4	4.9	3.9
Signal Type:											
All Value	11.0	8.4	8.0	7.1	6.2	5.6	4.9	4.8	4.7	4.1	3.5
All Momentum	8.7	7.8	5.1	5.3	4.7	4.0	3.4	2.8	2.6	1.7	0.7
All Carry	11.7	9.9	8.9	8.4	8.0	8.0	7.6	7.1	7.0	6.7	6.1
Strategy Category:											
Equity Value	14.3	11.0	7.7	6.9	6.6	5.7	4.5	4.7	4.3	3.7	3.6
Equity Momentum	12.4	8.0	3.5	3.8	2.8	2.3	1.8	1.5	1.1	0.5	−0.6
Equity Carry	13.0	12.7	11.0	11.1	10.8	10.1	9.7	8.6	7.6	6.9	5.7
Bond Value	15.1	11.5	11.2	8.8	7.0	6.4	5.8	5.3	5.0	4.2	3.6
Bond Momentum	8.6	6.9	5.6	5.4	6.3	6.5	6.2	5.9	6.2	5.7	5.1
Bond Carry	14.3	11.9	9.6	7.2	6.0	5.8	4.8	4.5	4.2	3.3	2.7
Currency Value	4.1	3.0	3.4	3.1	1.9	1.9	1.7	2.2	2.9	2.6	1.9
Currency Momentum	10.3	13.5	7.5	7.4	4.9	2.8	1.6	0.4	0.1	−1.9	−3.0
Currency Carry	17.3	10.7	9.2	8.2	8.4	9.4	9.0	8.4	9.5	10.4	10.7
Commodity Value	10.0	8.5	9.8	9.5	9.2	8.2	7.4	7.0	6.5	5.9	5.0
Commodity Momentum	3.6	3.0	3.9	4.4	4.7	4.5	4.1	3.6	2.9	2.4	1.3
Commodity Carry	2.3	4.4	5.9	7.2	6.7	6.8	6.9	6.9	6.7	6.3	5.3

Notes: This table reports the annualized average return over the last 20 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

Table D.9: Combined Performance: Average Return (Anlzd.), Last 15 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
All Portfolios:											
All	10.8	8.7	7.0	6.8	6.0	5.6	5.2	4.7	4.5	3.9	3.0
Asset Class:											
Equity All	13.4	10.6	7.9	8.3	7.3	6.2	5.4	5.0	4.3	3.5	2.5
Bond All	15.6	12.6	10.8	8.4	7.6	7.5	7.1	6.8	6.8	6.1	5.6
Currency All	10.3	8.5	5.0	5.5	4.5	4.0	3.7	2.5	2.8	2.3	1.4
Commodity All	3.9	3.1	4.3	4.9	4.7	4.5	4.5	4.4	4.2	3.7	2.6
Signal Type:											
All Value	11.8	8.9	9.2	8.8	8.0	7.2	7.0	6.7	6.6	6.1	5.4
All Momentum	7.7	7.1	3.0	3.7	2.8	2.3	1.8	1.5	1.1	0.2	−1.0
All Carry	12.9	10.0	8.8	7.8	7.4	7.2	6.7	5.9	5.8	5.4	4.6
Strategy Category:											
Equity Value	13.4	11.8	11.7	11.0	10.2	8.8	7.6	8.0	7.6	7.2	7.7
Equity Momentum	13.2	6.9	1.2	2.4	0.4	−0.4	−1.1	−1.4	−1.8	−2.6	−4.2
Equity Carry	13.6	13.2	10.8	11.5	11.4	10.2	9.6	8.5	7.2	6.0	4.1
Bond Value	18.8	14.4	14.2	10.9	9.2	8.8	8.5	8.0	7.6	6.6	6.0
Bond Momentum	9.8	8.6	6.4	6.1	7.1	7.3	7.3	7.2	7.4	7.0	6.5
Bond Carry	18.2	14.8	11.7	8.2	6.6	6.3	5.4	5.3	5.4	4.7	4.2
Currency Value	3.0	0.5	1.1	3.9	3.5	2.4	3.0	1.7	2.3	2.0	−0.1
Currency Momentum	7.1	13.9	4.5	5.8	2.4	1.3	0.3	−0.2	−0.8	−2.6	−3.8
Currency Carry	20.8	11.1	9.6	6.8	7.6	8.4	7.7	6.0	6.9	7.5	8.0
Commodity Value	12.0	9.0	9.7	9.5	9.2	8.9	9.0	9.0	9.0	8.7	8.1
Commodity Momentum	0.8	−0.8	0.0	0.4	1.1	0.8	0.6	0.4	−0.2	−1.0	−2.7
Commodity Carry	−1.2	1.0	3.1	4.6	3.9	3.7	3.9	3.9	3.7	3.3	2.3

Notes: This table reports the annualized average return over the last 15 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

Table D.10: Combined Performance: Average Return (Anlzd.), Last 10 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
All Portfolios:											
All	10.0	7.7	6.2	5.5	5.0	4.9	4.5	4.0	3.8	3.2	2.4
Asset Class:											
Equity All	14.4	11.5	8.4	8.0	7.3	6.1	5.0	4.4	3.6	2.9	1.4
Bond All	12.1	8.9	8.9	6.2	5.5	5.9	5.7	5.9	6.3	6.2	5.9
Currency All	10.3	7.7	3.6	3.1	3.0	3.9	3.6	2.5	2.1	1.0	0.4
Commodity All	3.2	2.7	4.1	4.5	4.3	3.9	3.6	3.4	3.4	2.7	1.8
Signal Type:											
All Value	12.2	9.8	9.2	7.9	7.7	7.1	6.6	6.3	6.2	5.7	5.2
All Momentum	6.7	5.4	2.1	1.9	1.4	1.4	1.0	0.8	0.6	−0.4	−1.6
All Carry	11.0	7.9	7.4	6.5	6.0	6.3	5.9	5.0	4.7	4.4	3.5
Strategy Category:											
Equity Value	10.8	9.0	9.1	7.3	7.4	6.2	5.1	5.1	5.0	4.6	3.9
Equity Momentum	15.8	10.6	4.0	3.8	2.3	0.9	−0.6	−1.5	−2.5	−3.0	−4.6
Equity Carry	16.7	15.0	12.1	13.0	12.2	11.2	10.5	9.5	8.3	7.1	4.9
Bond Value	15.7	9.2	10.8	7.7	6.6	6.9	6.6	6.1	6.5	6.2	6.5
Bond Momentum	8.1	8.2	6.4	5.3	6.2	6.6	6.7	7.1	7.8	7.6	6.6
Bond Carry	12.4	9.2	9.4	5.6	3.7	4.3	3.8	4.4	4.7	4.8	4.6
Currency Value	9.3	9.7	5.0	5.4	5.9	4.9	4.5	3.4	2.9	1.6	−0.1
Currency Momentum	1.9	4.1	−1.4	−0.9	−3.1	−1.8	−1.5	−1.3	−1.7	−3.8	−4.3
Currency Carry	19.5	9.3	7.2	4.8	6.2	8.4	7.9	5.4	5.0	5.3	5.4
Commodity Value	13.0	11.1	11.8	11.3	10.8	10.4	10.2	10.4	10.5	10.3	10.6
Commodity Momentum	1.1	−1.3	−0.7	−0.4	0.1	0.0	−0.6	−1.0	−1.3	−2.4	−4.3
Commodity Carry	−4.4	−1.9	1.1	2.6	1.9	1.3	1.2	0.9	0.9	0.3	−1.1

Notes: This table reports the annualized average return over the last 10 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

Table D.11: Combined Performance: Average Return (Anlzd.), Last 5 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
All Portfolios:											
All	13.2	8.6	5.9	5.3	4.8	4.6	4.0	3.9	3.9	3.3	2.3
Asset Class:											
Equity All	20.5	16.7	9.9	10.4	9.7	7.8	6.7	6.5	6.0	5.0	3.4
Bond All	10.6	4.0	1.8	−1.3	−1.7	0.0	0.1	1.5	2.9	3.7	4.2
Currency All	21.4	12.8	9.3	8.6	8.0	8.2	7.3	6.0	5.3	4.0	2.3
Commodity All	0.5	0.8	2.7	3.6	3.0	2.3	1.8	1.7	1.4	0.5	−0.8
Signal Type:											
All Value	17.3	10.8	9.6	8.8	7.0	6.5	5.9	5.8	5.7	4.8	4.5
All Momentum	8.1	6.1	1.7	1.7	1.1	1.1	0.9	1.2	1.2	0.5	−0.8
All Carry	14.3	9.0	6.4	5.6	6.2	6.2	5.2	4.8	4.7	4.7	3.2
Strategy Category:											
Equity Value	20.8	15.7	12.7	10.6	9.1	6.6	5.6	5.8	5.2	3.8	3.2
Equity Momentum	19.0	15.3	4.8	6.8	5.3	4.5	3.5	3.7	3.7	3.4	2.1
Equity Carry	21.5	19.2	12.1	13.6	14.7	12.4	11.0	10.0	9.0	8.0	5.0
Bond Value	18.2	6.5	3.7	0.0	−0.5	0.9	0.3	1.2	2.8	3.2	4.6
Bond Momentum	1.6	2.9	−0.3	−1.6	−0.8	1.2	2.4	3.7	5.8	6.6	6.0
Bond Carry	12.1	2.7	1.8	−2.2	−3.7	−2.0	−2.3	−0.5	0.1	1.3	2.0
Currency Value	20.8	11.4	10.3	13.3	9.5	9.4	8.8	7.3	6.5	4.2	2.2
Currency Momentum	11.8	9.5	6.0	4.1	2.3	2.0	1.8	1.8	0.6	−1.5	−2.8
Currency Carry	31.6	17.6	11.6	8.5	12.2	13.1	11.2	9.0	8.8	9.3	7.6
Commodity Value	9.4	9.6	11.6	11.1	9.9	9.3	8.7	8.7	8.5	7.9	8.1
Commodity Momentum	0.1	−3.5	−3.7	−2.6	−2.3	−3.4	−4.2	−4.4	−5.5	−6.6	−8.5
Commodity Carry	−8.1	−3.7	0.2	2.3	1.5	1.1	0.9	0.7	1.0	0.3	−1.9

Notes: This table reports the annualized average return over the last 5 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

Table D.12: Combined Performance: Volatility (Anlzd.), Last 20 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1
All Portfolios:											
All	11.6	11.0	10.5	10.0	9.3	8.4	7.9	7.2	6.7	5.9	5.2
Asset Class:											
Equity All	24.2	22.1	20.0	18.0	15.3	13.6	12.4	11.3	10.2	9.1	8.2
Bond All	19.7	18.8	14.9	13.6	12.6	11.6	10.8	10.1	9.4	8.7	8.2
Currency All	27.6	26.3	26.6	26.4	25.4	23.8	22.6	20.8	19.4	17.4	14.5
Commodity All	16.0	15.0	13.3	12.1	11.4	10.5	9.5	8.5	7.5	6.7	6.4
Signal Type:											
All Value	13.8	12.5	12.2	11.9	11.1	10.1	9.4	8.9	8.4	8.2	8.1
All Momentum	16.5	13.7	12.5	12.1	11.5	11.0	10.9	10.8	10.9	11.1	11.5
All Carry	14.3	13.1	12.7	12.3	11.9	11.5	11.2	11.1	11.0	10.7	10.4
Strategy Category:											
Equity Value	26.6	23.0	20.7	19.5	17.5	16.5	16.3	16.0	15.8	16.2	16.5
Equity Momentum	34.0	31.9	28.1	25.4	21.7	19.7	18.7	18.2	17.4	16.8	16.5
Equity Carry	28.2	23.8	22.8	20.6	19.0	18.2	17.4	16.6	16.1	16.0	15.9
Bond Value	19.7	19.9	16.3	16.2	15.6	14.6	13.9	13.3	12.4	11.4	10.4
Bond Momentum	21.8	18.3	15.0	13.9	13.5	13.5	13.8	14.0	14.1	14.4	14.9
Bond Carry	23.4	22.1	18.2	16.0	14.1	13.1	12.3	11.6	11.1	10.4	10.0
Currency Value	38.1	35.0	35.7	34.9	33.3	30.5	29.1	27.8	26.4	25.5	24.5
Currency Momentum	46.2	34.5	30.1	29.9	29.8	28.8	27.7	27.4	27.3	27.5	27.7
Currency Carry	36.0	33.1	32.3	32.2	32.4	32.1	32.1	32.0	31.9	31.9	30.7
Commodity Value	19.9	18.0	15.8	15.3	14.8	14.5	14.5	14.3	14.5	14.5	14.3
Commodity Momentum	19.6	17.5	15.8	15.0	14.8	14.8	14.6	14.5	14.3	14.2	14.4
Commodity Carry	20.0	17.9	15.9	14.6	14.3	13.8	13.2	12.6	12.1	11.7	11.6

Notes: This table reports the annualized volatility over the last 20 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.

Table D.13: Combined Performance: Sharpe Ratio, Last 20 Years

	Selectivity										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
All Portfolios:											
All	0.90	0.80	0.70	0.69	0.68	0.69	0.67	0.69	0.71	0.71	0.65
Asset Class:											
Equity All	0.54	0.49	0.37	0.40	0.44	0.44	0.43	0.43	0.43	0.41	0.35
Bond All	0.64	0.54	0.59	0.52	0.51	0.54	0.52	0.52	0.54	0.51	0.46
Currency All	0.38	0.34	0.25	0.24	0.20	0.20	0.18	0.18	0.21	0.21	0.22
Commodity All	0.33	0.35	0.49	0.58	0.60	0.62	0.64	0.69	0.72	0.73	0.60
Signal Type:											
All Value	0.80	0.68	0.66	0.60	0.56	0.55	0.51	0.54	0.56	0.50	0.44
All Momentum	0.53	0.57	0.41	0.44	0.41	0.37	0.32	0.26	0.24	0.15	0.06
All Carry	0.82	0.76	0.70	0.68	0.67	0.69	0.68	0.64	0.64	0.63	0.59
Strategy Category:											
Equity Value	0.54	0.48	0.37	0.35	0.38	0.35	0.28	0.30	0.27	0.23	0.22
Equity Momentum	0.37	0.25	0.12	0.15	0.13	0.12	0.09	0.08	0.06	0.03	−0.04
Equity Carry	0.46	0.53	0.48	0.54	0.57	0.56	0.56	0.52	0.47	0.43	0.36
Bond Value	0.77	0.58	0.69	0.55	0.45	0.44	0.42	0.40	0.40	0.37	0.35
Bond Momentum	0.39	0.38	0.37	0.39	0.47	0.48	0.45	0.42	0.44	0.40	0.34
Bond Carry	0.61	0.54	0.53	0.45	0.43	0.44	0.39	0.39	0.38	0.32	0.27
Currency Value	0.11	0.09	0.10	0.09	0.06	0.06	0.06	0.08	0.11	0.10	0.08
Currency Momentum	0.22	0.39	0.25	0.25	0.16	0.10	0.06	0.01	0.00	−0.07	−0.11
Currency Carry	0.48	0.32	0.29	0.25	0.26	0.29	0.28	0.26	0.30	0.33	0.35
Commodity Value	0.50	0.47	0.62	0.62	0.62	0.56	0.51	0.49	0.45	0.40	0.35
Commodity Momentum	0.19	0.17	0.25	0.30	0.31	0.30	0.28	0.25	0.20	0.17	0.09
Commodity Carry	0.11	0.24	0.37	0.49	0.47	0.49	0.52	0.55	0.55	0.54	0.46

Notes: This table reports the annualized Sharpe ratio over the last 20 years of our sample, October 2003–September 2023, for pair-selective CS portfolios at various selectivity levels. For each strategy category, each month, we sort base pairs by their θ score and include only the top S% of pairs in next month's CS portfolio of equity futures, where S ranges from 5% to 100%, with $S = 100\%$ corresponding with the benchmark linear-in-signal-rank weighting method that includes all possible pair strategies. Asset class, signal type, and overall portfolios are simple averages of their corresponding strategy category portfolios. θ is the empirical counterpart to model-implied conditional expected return (16), which is estimated over trailing windows (120 months for equities, 180 for bonds, 240 for currencies and commodities). Selectivity at the 5% level is indicated with blue bars and the benchmark with gray bars. Leverage multiples are fixed at 4.5 for equity portfolios, 7.5 for bond and currency portfolios, and 1.5 for commodity portfolios.