

Asymmetric Reversals

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Abstract

Short-term return reversal is one of the most robust asset-pricing anomalies, and is commonly linked to liquidity provision. We decompose individual firm stock returns into two distinct components: SYS, the component of returns that can be linked to systematic risk and public information releases; and an orthogonal residual RES. The RES component reverses, while the SYS component exhibits continuation. Moreover, the residual reversals are highly asymmetric: positive residual shocks reverse much more slowly than negative shocks. A return factor based on asymmetric idiosyncratic reversal subsumes the idiosyncratic volatility factor and a broad set of other short-horizon anomalies. Our findings suggest that asymmetric idiosyncratic reversal (AIR) is the primary driver of short-term return predictability.

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1 Introduction

Short-term return reversal is one of the oldest and most extensively studied anomalies in financial markets. Stocks that have recently underperformed tend to outperform over subsequent weeks, while recent winners tend to underperform. This pattern has been documented in a large body of empirical work beginning with [Lehmann \(1990\)](#), [Jegadeesh \(1990\)](#), and [Lo and MacKinlay \(1990\)](#). It is also supported by a rich theoretical literature in market microstructure. In these models, liquidity providers absorb temporary order imbalances and require compensation for bearing inventory, funding, and adverse-selection risks ([Grossman and Miller, 1988](#); [Kyle, 1985](#); [Glosten and Milgrom, 1985](#)). If liquidity providers have limited risk-bearing capacity, then, in these models, temporary price pressure generated by liquidity demand predicts future reversal. However, prices also respond to public news, and the order-flow market makers receive may be informed rather than liquidity-driven. Theory suggests that only price movements resulting from pure liquidity shocks should reverse, whereas those resulting from information should persist. Existing empirical work has recognized this distinction and shown that projecting individual firm returns onto proxies for new information can help to isolate the liquidity shocks: specifically, reversal strategies become more profitable when constructed using residual returns rather than raw returns ([Rosenberg et al., 1985](#); [Nagel, 2012](#); [Da et al., 2014](#); [Collin-Dufresne and Daniel, 2014](#)).

We build on this insight by developing a substantially richer decomposition of realized returns into two components. The first, which we denote SYS, controls for industry exposures, earnings-announcement effects, and more than 150 firm characteristics that capture firm exposure to common shocks. The second, which we denote RES, is the residual component. By stripping out a broad set of observable sources of systematic and public-information-driven return variation, RES should provide a sharper proxy for order-flow-driven shocks arising from private information and liquidity demand, which are the shocks liquidity providers intermediate.

We find that RES exhibits strong reversal. A simple reversal strategy that is long low-RES stocks and short high-RES stocks has earned 1.07% per month, four times the premium of the corresponding raw-return strategy. Given its substantially lower exposure to systematic risk factors, its historical Sharpe ratio is ten times larger.

These findings are consistent with the idea that, since it cannot be explained by systematic factor shocks or public information releases, the residual component RES is

likely driven either by order-flow shocks that originate from liquidity trading motives, or by trades based on private information. These, of course, are hard to disentangle for liquidity providers at the time the trades occur, resulting in risk to the liquidity providers who take the other sides of these trades. On average, a sizable fraction (10 to 20%) of that residual component reverses, compensating the liquidity providers for taking on this risk.

In contrast, we find that SYS, the component of returns due to systematic factor shocks and public information releases, exhibits continuation.

Thus, our decomposition reveals two distinct forces operating within short-term returns: SYS which exhibits short-term momentum and RES which exhibits short-term reversal. Traditional reversal strategies remain profitable because the reversal component dominates on average, but they mix together two economically distinct effects with opposite implications for expected returns.

Our central contribution is to show that residual reversals are highly asymmetric. Positive (RES^+) and negative (RES^-) residual shocks have markedly different impulse-response functions. RES^- shocks reverse rapidly: the temporary component dissipates over one month, and 29% of the return reversal occurs on the first day. RES^+ shocks reverse much more slowly (only 4% on the first day) and continue to predict future returns up to ten weeks later. At a monthly frequency, the bulk of negative return reversal has already occurred, and the positive reversal dominates. Properly accounting for this asymmetry dramatically strengthens the predictive content of residual returns and provides a unifying explanation for a range of short-horizon return anomalies. We construct a tradable factor based on asymmetric idiosyncratic reversals (AIR), which we denote by ASRES, that exploits the asymmetric reversal speed, outperforming the simple RES-sorted factor. This improved factor has a Sharpe ratio of 2.55, more than double that of the best-performing factor in the [Jensen et al. \(2023\)](#) database.¹

In addition to reversal, the academic literature has documented a host of other factors that also explain returns at short horizons. Most prominent is the idiosyncratic volatility (IVOL) effect documented in [Ang et al. \(2006, 2009\)](#), which is the phenomenon that high idiosyncratic volatility stocks subsequently earn unusually low

¹Over our sample, the factor with the highest Sharpe ratio in the JKP library is based on cash operating profits scaled by book assets (SR = 1.17). The original construction is due to [Ball et al. \(2016\)](#), and the factor returns are available at jkpfactors.com/data.

returns. The IVOL anomaly is a widely studied anomaly in the cross-section of stock returns and has motivated a wide range of competing explanations.

Yet IVOL is fundamentally linked to residual shocks that are large in magnitude. Stocks with unusually high idiosyncratic volatility will necessarily be those that have recently experienced large positive and/or large negative residual return realizations.

This connection creates an apparent tension. The residual-reversal evidence implies that stocks experiencing large negative residual shocks should subsequently outperform as prices recover from temporary liquidity shocks, while the IVOL anomaly, in contrast, predicts that stocks that have experienced unusually large residual variation should underperform. Because both positive and negative residual shocks contribute to idiosyncratic volatility, it is not immediately clear how these two sets of facts can coexist.

We show that the apparent contradiction is resolved by the asymmetry in residual reversals. Consider a stock that has experienced high idiosyncratic volatility (i.e., large positive and negative residuals) over the last month. Over the next few days, the large negative residuals will result in positive expected returns for this stock because of the rapid reversal of the negative shocks, but over the next month the slower reversal of the positive shocks will dominate, leading to a negative expected return for the coming month. Consistent with this hypothesis, we show that once we separately account for positive and negative residual return components, idiosyncratic volatility contains no significant incremental information about future returns. In [Fama and MacBeth \(1973\)](#) regressions, the IVOL premium disappears once we control separately for positive and negative residuals over the preceding month (RES^+ and RES^-). The IVOL anomaly therefore arises not because idiosyncratic volatility itself is priced, but because it is exposed to asymmetric residual reversals.

Our explanation for IVOL is thus distinct from existing explanations proposed in the literature that emphasize mispricing, limits to arbitrage, lottery demand, or asymmetric correction of overpricing and underpricing, as in [Stambaugh et al. \(2015\)](#). The asymmetry we document arises directly in the dynamic response of returns to positive and negative residual shocks. Rather than reflecting differences between overpriced and underpriced securities, it reflects differences in the speed with which positive and negative residual shocks are reversed. We show that this mechanism explains the predictive power of idiosyncratic volatility while remaining closely connected to the microstructure foundations of short-term reversal.

These insights extend beyond the IVOL anomaly. The literature has demonstrated that a variety of distinct characteristics—based on volatility, skewness, extreme returns, liquidity, trading costs, and trading activity—have independent power to explain short-horizon returns.² Hou and Loh (2016) show that, even jointly, this “short-term zoo” explains only a fraction of the IVOL premium. We show that accounting for the asymmetry in reversals subsumes all of the predictability associated with these characteristics. The one-month return predictability associated with each of these characteristics disappears once we account for the asymmetries in idiosyncratic reversals (AIR), and the momentum in SYS. This finding helps to unify a broad set of short-horizon anomalies previously investigated independently.

ASRES – an AIR-based trading strategy – earns a Sharpe ratio of 2.55 and a CAPM-based information ratio of 2.6 (both annualized). This high level of performance begs the question of why new investors did not enter the market and compete away, or at least reduce these high returns. We have been careful to ensure that the ASRES is implementable: the prices that we use are from CRSP and since 2000 come from closing auctions (Bogousslavsky and Muravyev, 2023). Today investors can participate directly in closing auctions and in so doing buy or sell at the closing auction price. That is, they don’t pay a bid-ask spread. Brokerage commissions are zero for most brokers. Data access was historically costly, but the required data are now available at low cost. Moreover, we are careful to ensure that an investor could have accessed the required data at least one trading day prior to the date on which the investor would have had to trade. Thus, in principle, this strategy should have been implementable over the past several decades, and sufficiently small trades would have been executed near the closing price.

However, historically high brokerage commissions, wide bid-ask spreads, and expensive data access would have raised the effective cost of entry, effectively granting

²Our tests use thirteen one-month characteristics: Fama–French three-factor idiosyncratic volatility and return volatility (Ang et al., 2006); raw return skewness (Barberis and Huang, 2008; Mitton and Vorkink, 2007; Bali et al., 2016); Fama–French three-factor idiosyncratic skewness (Mitton and Vorkink, 2007; Boyer et al., 2010); one-month CAPM residual coskewness (Harvey and Siddique, 2000); the maximum daily return over the formation month (Bali et al., 2011); the average of the five largest daily returns (Bali et al., 2017); the average of the five largest daily returns scaled by return volatility (Asness et al., 2020); lagged return (Jegadeesh, 1990); Amihud illiquidity (Amihud, 2002; Han and Lesmond, 2011; Hou and Loh, 2016); zero-trading days (Lesmond et al., 1999; Liu, 2006; Han and Lesmond, 2011); a high–low effective-spread estimate based on Corwin and Schultz (2012), motivated by trading-cost evidence (Amihud and Mendelson, 1986; Hou and Loh, 2016); and average daily share turnover, inspired by lower-frequency evidence on turnover and expected returns (Datar et al., 1998; Lee and Swaminathan, 2000; Chordia et al., 2001).

market makers monopolistic power and sustaining the premium we document. Finally, awareness itself is a prerequisite for entry—it is plausible that few investors knew of these patterns, especially in earlier decades. Consistent with declining fixed costs of entry, the Sharpe and information ratios of the AIR strategy have fallen over time, and we anticipate this trend will continue as entry increases further.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 introduces our return decomposition and evaluates its ability to separate systematic and residual variation. Section 4 studies the predictive content of SYS and RES. Section 5 introduces asymmetric idiosyncratic reversal and shows how it resolves the idiosyncratic volatility anomaly and spans a broader set of one-month short-term characteristics. Section 6 examines the dynamics of residual reversals at daily horizons. Section 7 develops implementable trading strategies based on asymmetric residual reversals. Section 8 concludes.

2 Data

We collect daily and monthly returns, market capitalizations, trading volumes, and shares outstanding from the CIZ version of CRSP. Our sample consists of U.S. common stocks with valid market equity and regular trading status on NYSE, Amex or NASDAQ as of the month we form portfolios.³ The sample period ranges from January 1972 to December 2022.⁴ We also require stocks to have a valid Fama-French 49 industry classification and to be sufficiently large to enter our sample. Specifically, we add stocks to the investable sample when they exceed 0.003% of the aggregate market capitalization, and drop them if they fall below 0.002%. This filter addresses potential distortions in factor portfolio returns due to return outliers in small and illiquid stocks. Similar to us, [Kozak and Nagel \(2024\)](#) discard stocks below 0.0025% of total market capitalization. Hysteresis around this threshold helps limit the trading volume due to stocks dropping in and out of the sample. Figure [A.1](#) plots our market equity cutoffs over time.

³These are the stocks with share type equal to “NS”, security type equal to “EQTY”, security subtype equal to “COM”, issuer type “ACOR” or “CORP”, U.S. incorporation, primary exchange flag “N”, “A”, or “Q”, active trading status, and conditional type “RW”. These filters parallel the requirement of a share code of 10 or 11, and exchange code 1, 2, or 3 in the legacy CRSP version. The returns CRSP provides in its CIZ version are adjusted for delisting events.

⁴We begin our sample in 1972 since it is the first year with reliable coverage of earnings-announcement dates in Compustat.

We gather earnings-announcement dates from Compustat quarterly files. Compustat is also our primary source for SIC codes, which we use for industry definitions. We assume the Compustat SIC code is known after a three-month lag. We consider the Compustat SIC code current if it is less than 18 months stale. Otherwise, we use SIC codes from CRSP. We forward-fill missing values in the SIC codes constructed in this way for up to 12 months. We then use these SIC codes to assign stocks to industry portfolios, following the 49 industry classification of [Fama and French \(1997\)](#).

We rely on an extensive set of firm characteristics to capture common variation in excess returns. We use 151 of the characteristics made available by [Jensen et al. \(2023\)](#) (JKP). We follow [Kozak and Nagel \(2024\)](#) and [Kozak \(2020\)](#) and rank transform, center, and standardize these characteristics to limit the influence of outliers. Starting with the realizations c of characteristic k at month-end m , we first rank the cross-section. We then scale the resulting ranks by the number of stocks with valid characteristic realizations and remove the mean.

$$rc_{i,k,m} = \frac{\text{rank}(c_{i,k,m})}{n_{k,m} + 1} - \frac{1}{2} \quad (1)$$

where $n_{k,m}$ is the number of stocks with valid characteristic realizations for characteristic k at month-end m . In case of ties, we assign stocks the average rank. These centered ranks are positive for high and negative for low characteristic realizations. We then fill missing values with zero and normalize by the average absolute rank.

$$x_{i,k,m} = \frac{rc_{i,k,m}}{|rc_{i,k,m}|}. \quad (2)$$

We collect these transformed characteristics in the matrix $\mathbf{X}_m$. To reduce noise in cross-sectional regressions, we apply three additional filters. First, we drop discrete-valued characteristics with few possible values. Factor portfolios formed based on these characteristics can have unrealistic turnover, as several securities sharing the same rank can move from the short leg to the long leg (and vice versa) due to small movements in the characteristic distribution. We drop the characteristics that JKP label as “ni_inc8q” (number of consecutive quarters with increased company earnings, originally due to [Barth et al. \(1999\)](#)), and “f_score” (Piotroski F-score, originally due to [Piotroski \(2000\)](#)). This leaves us with 151 firm characteristics.

Second, at each month-end m , we only include characteristics with sufficiently many observations. We add characteristics to $\mathbf{X}_m$ when 40% of the stocks in our

sample have valid observations, and remove them when the number of valid characteristic realizations drops below 20%. Third, after this coverage screen, we remove near-collinear characteristics from $\mathbf{X}_m$. If two characteristics have an absolute cross-sectional correlation of at least 99%, we drop the one with the shortest tenor as of that month. We reintroduce the omitted characteristic only when the correlation falls to 97.5% or below. This filter only uses information up to month-end m to choose the representative characteristic within near-collinear pairs, and it is thus free of look-ahead bias. Figure A.2 summarizes the characteristics included in $\mathbf{X}_m$ by date and JKP theme.

2.1 Additional characteristics

At several points in the paper, we use the set of characteristics underpinning the six-factor model of Fama and French (2020) (FF6) as controls in our cross-sectional regressions. These characteristics are: market beta estimated over the previous 60 months, the logarithms of size (market equity) and book-to-market, operating profitability, investment, and momentum (i.e. the return over the previous year excluding the most recent month). We use the JKP replications for these characteristics, and we do not standardize them. Time-series regressions based on the FF6 model use the return factors available on Kenneth French’s website instead.

We use our own replications of short-term characteristics that have been shown to capture part of the idiosyncratic volatility premium. To this end, we start with the short-horizon return, distribution, liquidity, and trading activity variables emphasized in this literature, with IVOL as the prominent case study. We discuss the construction of these variables in Appendix E.

3 Decomposing realized returns

We adopt the hypothesis that the premium earned by short-term reversal strategies reflects the compensation demanded by risk-averse market makers for providing liquidity (Jegadeesh and Titman, 1995; Nagel, 2012; Da et al., 2014; Collin-Dufresne and Daniel, 2014; Dai et al., 2024). Uninformed investors demand liquidity, in the sense that they buy or sell securities for reasons unrelated to information, and in so doing put temporary pressure on prices. Market makers accommodate this order flow, expecting to later unwind their resulting inventory imbalances at a profit by trading with

slower moving liquidity providers. In contrast, to the extent that they can discriminate between informed and uninformed demand, these market makers do not supply liquidity for information-based trades, as these trades will have a permanent impact on prices, and they would not be able to unwind these positions at a profit.

This hypothesis suggests that the component of returns related to public news or systematic risk factors should be largely permanent. Instead, the residual component of returns not explained by systematic factors or public news should revert to the extent that it is driven by uninformed order-flow. In this section, we attempt to disentangle these two components.

The premium associated with the short-term reversal factor decays rapidly, consistent with its transitory and liquidity-related interpretation. Therefore, in our decomposition, we focus on daily returns rather than monthly returns. We run cross-sectional regressions of day $t + 1$ excess returns on the JKP characteristics described in the previous section. For the $t + 1$ regression in month m , the $(N \times K^X)$ matrix $\mathbf{X}_t$ contains characteristics measured at the end of month $m - 1$ and is held fixed throughout month m . These characteristics received attention in the literature because they carry conditioning information that helps to explain differences in *average* returns. This is not our goal here. Rather, we want to project realized returns onto systematic factors that capture either priced or unpriced variation. From the perspective of a risk-averse market maker, exposure to these factors increases inventory risk but does not contribute to market-making proceeds.

We supplement the matrix of characteristics with industry assignments, which are known to explain a large portion of the covariance matrix of realized returns. Each row of the $(N \times K^I)$ industry matrix $\mathbf{I}_t$ is a vector of indicator variables. A value of one denotes that firm-row i belongs to the industry-column k (and a value of zero denotes that the firm does not operate in industry k). Since all firms are assigned to one and only one industry, each row contains one 1, and $K^I - 1$ zeros, and thus we have no need for an intercept in the regression.

$$\mathbf{r}_{t+1} = \mathbf{I}_t \mathbf{r}_{t+1}^I + \mathbf{X}_t \mathbf{r}_{t+1}^X + \boldsymbol{\varepsilon}_{t+1} \quad (3)$$

Consistent with the standard [Fama and MacBeth \(1973, FM\)](#) interpretation: $\mathbf{r}_{t+1}^I$ and $\mathbf{r}_{t+1}^X$ are the realizations of latent factors that must be estimated, and which ideally capture all systematic variation in returns; $\mathbf{I}_t$ and $\mathbf{X}_t$ are observable matrices which

give each stock's loadings on these latent factors; and ε_{t+1} is the N -vector of residual/idiosyncratic returns, which are assumed to be orthogonal to the factors.

The matrix of characteristics we use here, from JKP, is selected not because these characteristics explain average return differences, but rather because they capture common variation in realized returns. Similarly, we use industry memberships because these are well known to capture common industry-level variation in realized returns (Rosenberg and McKibben, 1973; Daniel et al., 2020). The JKP characteristics that we use for our empirical results are roughly four times as numerous as the characteristics in Kozak and Nagel (2024).⁵

Following standard FM, we estimate the factor realizations each day using a cross-sectional regression of realized returns on the matrix of factor loadings $\mathbf{Z}_t = [\mathbf{I}_t \ \mathbf{X}_t]$, which here are the industry memberships and characteristics. We run WLS regressions with a diagonal weighting matrix $\mathbf{\Omega}_t = \text{diag}(\omega_{1,t}, \dots, \omega_{N,t})$. The weights $\omega_{i,t} = \text{ME}_{i,t}^W / \sum_{j=1}^N \text{ME}_{j,t}^W$ are stock market equities at the beginning of the month, winsorized to the 80th NYSE percentile and normalized by aggregate market equity computed in this way.

The resulting $(K \times 1)$ vector (where $K = K^I + K^X$) of regression coefficient estimates is then:

$$\hat{\mathbf{f}}_{t+1} = \begin{bmatrix} \mathbf{r}_{t+1}^I \\ \mathbf{r}_{t+1}^X \end{bmatrix} = \underbrace{(\mathbf{Z}_t' \mathbf{\Omega}_t \mathbf{Z}_t)^{-1} \mathbf{Z}_t' \mathbf{\Omega}_t}_{\equiv \mathbf{W}_t'} \mathbf{r}_{t+1} = \mathbf{W}_t' \mathbf{r}_{t+1}$$

Since the elements of $\mathbf{Z}_t$ are in the agent's information set at the start of period $t + 1$, the k th estimated coefficient in $\hat{\mathbf{f}}_{t+1}$ is the return to a characteristic-based factor portfolio with weight vector given by the k th row of the $(K \times N)$ weight matrix $\mathbf{W}_t'$. Note that $\mathbf{W}_t' \mathbf{Z}_t = \mathbf{I}$, so the portfolio with the k th weight vector has unit exposure to the k th characteristic/industry, and zero exposure to all others (Grinold and Kahn, 2000).

Note that our choice of $\mathbf{\Omega}_t$ results in larger portfolio weights for large-cap securities that are more easily traded, and in weights closer to zero for small-cap securities.⁶

⁵In principle, it would be useful to include all publicly available characteristics that help explain co-movements across stocks.

⁶Jensen et al. (2023) advocate for value-cap-weighted time-series factors. In the context of cross-sectional regressions involving individual stocks, several studies document that OLS overweights micro-cap stocks, producing misleading results (Fama and French, 2008; Green et al., 2017; Hou et al., 2020). Ideally, if it were known, we would use for $\mathbf{\Omega}_t$ the inverse of the covariance of returns $\Sigma := \text{Cov}_t(\mathbf{r}_{t+1}) = E_t[(\mathbf{r}_{t+1} - E_t[\mathbf{r}_{t+1}])(\mathbf{r}_{t+1} - E_t[\mathbf{r}_{t+1}])']$ (or equivalently for the factor construction the inverse of the covariance of residual returns $\Sigma_\varepsilon := E_t[\varepsilon_{t+1}\varepsilon_{t+1}']$) in which case the $\mathbf{W}_t$ would be the factor-mimicking

The vector of time t fitted returns for the N individual assets is given by:

$$\hat{r}_{t+1} = Z_t \hat{f}_{t+1} = \underbrace{Z_t (Z_t' \Omega_t Z_t)^{-1} Z_t' \Omega_t}_{\equiv w_t' = Z_t W_t'} r_{t+1} = w_t' r_{t+1}, \quad (4)$$

Again, these fitted returns are the returns to N portfolios with weights given by the rows of the matrix w_t' . Row i is the linear combination of the K characteristic portfolios in W_t which matches the characteristics of asset i , based on its characteristics (and industry membership). $\varepsilon_{t+1} = r_{t+1} - \hat{r}_{t+1}$ is the vector of residual returns that are not explained by the characteristics and industries. The residuals ε_{t+1} have zero weighted exposure to the K characteristics/industries.

Equipped with the panel of regression residuals ε_{t+1} , isolating the liquidity component of these shocks requires us to further remove firm-specific but information-driven return variation. We focus on earnings-announcement dates, since we expect price moves occurring around these dates to be largely reflective of new information being impounded into prices.⁷ Let $\mathcal{E}_i$ denote the daily earnings-announcement window for stock i , namely the set of return dates that fall within one trading day of an earnings announcement. If an observation falls within this window, we set residuals to zero for that observation. We denote by $\tilde{\varepsilon}_{t+1}$ the modified residuals obtained in this way. We add the residual component removed inside earnings-announcement windows to the systematic component $\tilde{r}_{t+1}$, because it likely captures information-driven variation in returns rather than liquidity shocks. We define

$$\tilde{\varepsilon}_{i,t+1} = \begin{cases} 0 & t+1 \in \mathcal{E}_i, \\ \varepsilon_{i,t+1} & t+1 \notin \mathcal{E}_i, \end{cases} \quad (5)$$

$$\tilde{r}_{i,t+1} = r_{i,t+1} - \tilde{\varepsilon}_{i,t+1}. \quad (6)$$

In the remainder of the paper, we suppress firm and time subscripts and refer to these components as simply ε , $\tilde{\varepsilon}$, r , and $\tilde{r}$ for legibility, when no ambiguity arises. By construction, $\tilde{r}$ equals the systematic component outside earnings-announcement windows and the full excess return inside earnings-announcement windows. The returns

portfolios with maximum explanatory power in the sense that they would have minimum residual risk. Since neither Σ nor Σ_ε are known however, we follow a long tradition to use WLS instead ([Grinold and Kahn, 2000](#)).

⁷In principle, this can be further improved on by controlling for other event dates corresponding to material information releases, such as unscheduled earnings announcements, merger announcements, ... We leave this for future research.

$\tilde{r}$ and $\tilde{\varepsilon}$ can be viewed as excess returns on investable portfolios. To earn $\tilde{r}$, an investor should hold stock i within earnings-announcement windows, and instead hold the characteristic-based factors and industry portfolios proportional to stock i 's characteristic realizations at all other times. Conversely, holding the risk-free asset within earnings-announcement windows and holding stock i while hedging away the systematic component at all other times yields the residuals $\tilde{\varepsilon}$. [Da et al. \(2014\)](#); [Collin-Dufresne and Daniel \(2014\)](#); [Dai et al. \(2024\)](#), among others, also show that removing the component of returns due to earnings announcements improves the performance of short-term reversal strategies.

3.1 Relationship with time-series models

Related to our analysis here, [Da et al. \(2014\)](#); [Nagel \(2012\)](#); [Blitz et al. \(2013\)](#) construct residual reversal factors by sorting stocks on factor model residuals. More broadly, a large literature in empirical asset pricing identifies anomalies in returns sorted by different moments of past residual returns ([Ang et al., 2006, 2009](#); [Mitton and Vorkink, 2007](#); [Boyer et al., 2010](#); [Herskovic et al., 2016](#); [Blitz et al., 2011](#)).

The common feature of these papers is that they estimate idiosyncratic returns by running separate time-series regressions for each individual stock's daily realized excess returns on a set of common factor returns, typically the [Fama and French \(1993\)](#) three factors (FF3). For instance, [Ang et al. \(2006\)](#) regress daily individual stock returns on the daily FF3 factors returns realized over the previous month, and use the volatility of the daily idiosyncratic returns obtained in this way as a sorting variable. We deviate from their approach and study cross-sectional regression residuals. This modeling choice presents several advantages. First, it allows us to consider a broader set of characteristics and industry exposures, beyond the market, size and value. The richer set of characteristics allows us to better pin down the idiosyncratic component of returns.

Second, somewhat counterintuitively, our characteristics specification (3) is more parsimonious than the FF3 model. For example, implementing stock-level FF3 regressions requires estimating four parameters for each stock and month. In contrast, we estimate roughly 200 coefficients per trading day. Over our sample, the parameter count of the FF3 model is more than twice that of our decomposition (3). Lastly, the residual returns from our cross-sectional regressions correspond to investable returns. According to our specification, the asset weight vector for the portfolio which opti-

mally hedges the systematic risk of each security i during month $t + 1$ is given by the i 'th row of the matrix w_t' as defined in equation 4. Because all of the elements of Z_t are observable as of the end of month t , so is the makeup of this hedge portfolio.

We can thus interpret the residual returns ε_t as the shocks a market maker accommodates when providing liquidity and hedging systematic risk. Conversely, this interpretation does not hold under time-series regressions, at least as typically applied, because implementing the hedge portfolio requires knowledge of the factor betas, which are functions of the full set of daily returns in month $t + 1$.

How much of the return variance does the decomposition in equation (3) capture? Figure 1 plots the explained fraction each year y . We show the total adjusted R_y^2 :

$$R_y^2 = 1 - \frac{\widetilde{\text{RSS}}_y / (N_y - K_y)}{\widetilde{\text{TSS}}_y / (N_y - D_y)}, \quad (7)$$

Recall that $\omega_{i,t}$ denotes the WLS weights used in the regression (3). The counts N_y , K_y , and D_y are respectively the number of observations, estimated parameters, and trading days in year y . The quantities $\widetilde{\text{TSS}}_y$ and $\widetilde{\text{RSS}}_y$ are the (weighted) total and residual return variation in that year:

$$\widetilde{\text{TSS}}_y = \sum_{t \in y} \sum_{i=1}^N \omega_{i,t} (r_{i,t} - \bar{r}_{\omega,t})^2, \quad (8)$$

$$\widetilde{\text{RSS}}_y = \sum_{t \in y} \sum_{i=1}^N \omega_{i,t} \varepsilon_{i,t}^2, \quad (9)$$

where $\bar{r}_{\omega,t} = \sum_{i=1}^N \omega_{i,t} r_{i,t}$ is the weighted cross-sectional mean return on day t .

The left panel of Figure 1 shows that the restricted characteristics-only specification has an average annual R^2 of roughly 17%, while the baseline characteristics-and-industries specification has an average annual R^2 of roughly 20%. Including industry assignments therefore increases average fit by roughly 3 percentage points, with the annual gap reaching about 5 percentage points in 2015. The baseline specification peaks at roughly 40% at the end of the sample, and model performance rises sharply during market downturns, including the Great Financial Crisis, the COVID crash, and the end of the sample. The right panel compares these cross-sectional specifications to the stock-by-stock FF3 benchmark. Both cross-sectional models outperform the FF3

residualization in every sample year, with the exception of the characteristics-only model in 1987. The average annual spread is roughly 8 percentage points for the restricted specification and roughly 11 percentage points for the baseline specification. This evidence supports the use of the large cross-sectional regression (3) to capture systematic variation in returns.

Note that subtracting the number of parameters K_y in equation (7) would be an exact degree of freedom correction under a correctly specified GLS, where the regression weight matrix Ω_t would be proportional to the inverse covariance matrix, so that the transformed errors are homoskedastic and mutually uncorrelated. Since that matrix is not known, however, we choose a weighting scheme inversely related to market capitalization, which leads to portfolio weights with desirable features (see footnote 6). Internet Appendix Figure A.3 shows the same upward trend in variance explained over time when using OLS regressions, both in absolute terms and relative to the FF3 specification.

In the Internet appendix B, we provide further diagnostics and discussion of the source of variation in the RSS_y over time and discuss the connection to the recent literature on the time-series trend in idiosyncratic volatility (Campbell et al. (2001); Xu and Malkiel (2003); Campbell et al. (2023)).

4 Short-term momentum and reversal

We next study the relationship between a firm’s lagged systematic and residual return components— $\tilde{r}$ and $\tilde{\varepsilon}$ —and its expected future return. We show that the residual component reverses, while the systematic exhibits continuation/momentum. That is, the expected future return is negatively related to lagged $\tilde{\varepsilon}$ s and positively related to lagged $\tilde{r}$ s.

To begin, we compute monthly sums of the two daily components, which we then use to forecast future monthly returns. Consistent with the definition of $\tilde{\varepsilon}$ in equation (5), earnings-announcement-window residuals are zero. In forming the monthly sum, we exclude the last trading day of the month. The monthly returns we forecast are close-to-close, so skipping a day ensures that $\tilde{r}$ and $\tilde{\varepsilon}$ are in the agent’s information set one trading day before the start of the monthly trading window. Skipping one day between measurement and portfolio formation also reduces the influence of bid-ask bounce and non-synchronous trading (Lehmann, 1990).

We denote by $\mathcal{D}_{i,m}$ the set of active trading days in month m for stock i , excluding the last day of the month. Our monthly measures are then

$$\text{RES}_{i,m} = \sum_{t \in \mathcal{D}_{i,m}} \tilde{\varepsilon}_{i,t}, \quad (10)$$

$$\text{SYS}_{i,m} = \sum_{t \in \mathcal{D}_{i,m}} \tilde{r}_{i,t}, \quad (11)$$

Because daily excess returns are the sum of their systematic and residual components, $\text{RES}_{i,m}$ and $\text{SYS}_{i,m}$ add up to $\text{RET}_{i,m}$.

Each month, we form quintile portfolios both based on RES and on SYS, and using NYSE breakpoints. Table 1 presents the pre- and post-formation (month m and $m + 1$) average returns, FF six-factor alphas, and a number of other portfolio characteristics for these portfolios.

If SYS and RES are highly correlated in the cross-section, then sorting independently on SYS and RES might not separate out the two components. The first two rows show that this is not the case. The RES-sorted portfolios have an average RES spread of 17.40%, and a -2.35% spread in the SYS. The SYS sorts are also effective. Both sorts also produce large pre-formation return spreads. Thus both sorting variables separate recent winners from recent losers, and the decomposition identifies which component of the one-month return each sort captures.

The post-formation (month $m + 1$) average returns exhibit the differences in the links between these components and future returns. The RES sort produces evidence of short-term reversals: month $m + 1$ returns and alphas are strongly negatively correlated with RES_m . But, for the SYS sorts the relationship flips and the correlation is positive. The relationships are monotonic and strong in each sort, but they are decreasing for RES sorts and increasing for SYS sorts. The Newey–West t-statistics on the High–Low average-return/alpha are $-8.51/-7.42$ for the RES sorts and $5.35/4.39$ for the SYS sorts. This finding rationalizes why standard portfolio sorts involving one-month raw returns find evidence of reversal rather than momentum.

Table 1 speaks directly to a recent literature that finds pockets of short-term momentum in specific subsets of stocks. [Medhat and Schmeling \(2022\)](#) document that stocks within the highest share-turnover decile exhibit short-term momentum, while the remainder of the cross-section displays the familiar short-term reversal pattern. Their results are consistent with a liquidity interpretation of the short-term reversal

anomaly. Supplying immediacy in liquid stocks is less risky, because offsetting order flow arrives quickly. Therefore, market makers operating in this segment earn lower profits, and the reversal effect is weaker among liquid stocks because it represents the footprint of these profits in stock returns. Sorting on raw returns at a one-month frequency *within that subset of liquid stocks* thus picks up momentum, rather than reversal. Consistent with this notion, [Dai et al. \(2024\)](#) emphasize that the return reversals take place over the span of about a week among liquid stocks.

Our results imply that short-term momentum is a broader property of the cross-section. One-month returns contain both continuation and reversal forces, and only the systematic component generates momentum. Sorting on raw returns only captures this momentum effect among stocks that happen to have a small residual component. We show in Table 1 that the typical stocks in the two extreme SYS quintiles have similar share turnover, size, liquidity, and idiosyncratic volatility, which [Dai et al. \(2024\)](#) study as determinants of the timing and strength of reversals. These patterns further highlight that the short-term momentum effect we demonstrate is not driven by systematic differences in these characteristics.

Our results also relate to a large literature on medium-term momentum that skips the most recent month in the construction of the one-year momentum signal. This common practice aims to sterilize the countervailing effect of short-term reversals operating at the one-month frequency. Evidence in Table 1 suggests that a better momentum signal can be obtained by directly isolating the systematic component of returns, rather than skipping the most recent month. Since the reversal anomaly is short-lived, the confounding effect of liquidity-driven reversals past the one-month horizon is likely to be small for most stocks. Sorting on SYS also links our results to industry and factor momentum because it sorts stocks by exposure to recently successful industries and characteristic-based factors ([Moskowitz and Grinblatt, 1999](#); [Ehsani and Linnainmaa, 2022](#)).

Lastly, Table 1 shows a monotonically increasing, although mild, relationship between SYS and earnings surprises, which we proxy through the standardized unexpected earnings (SUE) measure. This measure is the change in firm earnings over four quarters, normalized by the standard deviation of earnings over the previous eight quarters. High systematic-return stocks have higher SUE than low systematic-return stocks, while the residual sort does not show a discernible pattern for SUE. This evidence validates the adjustment in equation (6) where we add residual shocks occurring within earnings-announcement windows to the systematic component. The in-

crease in SUE as recent systematic returns increase is consistent with the post-earnings-announcement drift (PEAD) anomaly. Firms with positive earnings surprises tend to also have high announcement residuals. The fact that stocks with high recent SYS outperform over the following month reflects in part that investors under-react to earnings-announcement disclosures. The earnings-announcement residuals predict continuation rather than liquidity reversal (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990).

Table 1 measures the gross expected-return relation associated with lagged return components. However, it is a high turnover strategy: one-way monthly portfolio turnover is about 76% to 80% across quintiles. In our liquidity-provision interpretation, the reversal premium compensates investors who accommodate order-flow shocks. A long-short strategy formed after observing the lagged components measures this expected-return relation. We next show that the High–Low spreads in Table 1 can explain the short-horizon predictability results documented in the literature.

5 AIR and the short-term factor zoo

Table 1 shows that monthly idiosyncratic shocks reverse strongly in the following month. In this section, we document a sign asymmetry in this idiosyncratic reversal effect. In Section 6, we explore this asymmetry further, and show that it results from slower reversal in response to positive than negative idiosyncratic shocks at a daily horizon. This section is devoted to showing that this asymmetry explains the idiosyncratic volatility (IVOL) anomaly (Ang et al., 2006, 2009) and other related short-horizon anomalies.

Empirically, high-IVOL stocks markedly underperform low-IVOL stocks over the following month. This effect poses a longstanding puzzle in asset pricing: in complete, frictionless markets idiosyncratic risk should not command a premium, while incomplete-information and trading-cost models predict positive compensation for residual risk rather than the negative IVOL premium (Merton, 1987; Hirshleifer, 1988). Perhaps because of this, the literature has investigated a set of other characteristics, motivated through different economic mechanisms, that capture part of the IVOL premium, but which do not fully explain the IVOL premium (Hou and Loh, 2016).

Here, we show that the asymmetric idiosyncratic reversal effect we document subsumes the IVOL premium, and subsumes or reverses the premium associated with these alternative characteristics.

5.1 AIR and IVOL

Ang et al. (2006) document that stocks' future one-month returns are strongly negatively related to the volatility of the daily idiosyncratic returns they experienced in the previous month (IVOL).⁸ There is an inherent tension between this finding and the idiosyncratic reversal effect we document in Table 1: if future returns were just related to IVOL, then both extreme positive and extreme negative idiosyncratic returns would result in higher IVOL, and lower future returns. In contrast, the results of Table 1 suggest a monotonic relation between lagged idiosyncratic returns and future return. To reconcile the two effects, we separate out the predictability associated with positive and negative idiosyncratic shocks. We define:

$$\text{RES}_{i,m}^+ = \sum_{t \in \mathcal{D}_{i,m}} \max\{\tilde{\varepsilon}_{i,t}, 0\}, \quad (12)$$

$$\text{RES}_{i,m}^- = \sum_{t \in \mathcal{D}_{i,m}} \min\{\tilde{\varepsilon}_{i,t}, 0\}, \quad (13)$$

where we again zero out residuals in earnings-announcement windows and we skip the last trading day of the month. Based on these definitions $\text{RES}^+ \geq 0$ and $\text{RES}^- \leq 0$. Note also that, if monthly reversal were linear, a projection of future returns onto RES^+ and RES^- would yield the same negative projection coefficient.

We compute idiosyncratic volatility from the raw daily residual series:

$$\text{IVOL}_{i,m} = \sqrt{\frac{1}{n_{i,m} - 1} \sum_{t \in \mathcal{D}_{i,m}} (\varepsilon_{i,t} - \bar{\varepsilon}_{i,m})^2}. \quad (14)$$

As we did in calculating RES, we skip the last day of the month when computing IVOL to ensure that portfolios based on this signal are tradable. We do not, however, exclude earnings-announcement days from the IVOL computation, in keeping with the literature on the IVOL anomaly. Thus IVOL uses the raw cross-sectional-regression

⁸Ang et al. (2006) use the residuals from FF3 regressions to calculate their IVOL measure. Below, we use cross-sectional regressions with JKP characteristics and industries, as described earlier. We confirm below that the IVOL effect remains strong despite these methodological differences.

residual ε , whereas RES^+ and RES^- use the earnings-adjusted residual $\tilde{\varepsilon}$. We show in the Internet Appendix D.1 that our results are not sensitive to applying the same earnings-announcement exclusion to IVOL.

To examine the relationship between the signed residual returns and IVOL, we run monthly Fama–MacBeth regressions of IVOL on the signed residuals:⁹

$$\text{IVOL}_{i,m} = -0.0003 + 0.078 \text{RES}_{i,m}^+ - 0.067 \text{RES}_{i,m}^- + \eta_{i,m}, \quad \bar{R}_{\text{adj}}^2 = 81.6\%. \quad (15)$$

$\begin{matrix} [-7.41] & [72.06] & [-126.17] \end{matrix}$

The numbers in brackets are Newey–West t -statistics based on the time series of monthly WLS coefficients. Consistent with the intuition presented above, higher magnitude positive and negative residuals on average are associated with higher IVOL. (Since RES^- is always non-positive, higher $|\text{RES}^-|$ is associated with higher IVOL). The time-series average of the cross-sectional R_{adj}^2 coefficients is 81.6%. This R^2 is large but, as we will see in the next subsection, there is sufficient independent variation to allow us to estimate which of the three variables best forecast future monthly returns, and in section 6 we will show how asymmetries in the decay rates of daily impulse response functions result in asymmetries in the forecasting power for RES^+ and RES^- , with RES^+ dominating at longer horizons so as to explain the monthly IVOL anomaly.

5.2 Spanning IVOL with AIR

We next examine the ability of IVOL and the signed residual components to forecast future monthly returns. We posit that returns over the coming month are a function of RES^+ , RES^- , and IVOL, measured at the end of the preceding month, and a set of controls. That is:

$$r_{i,m+1} = \lambda_m^0 + \lambda_m^{\text{IVOL}} \text{IVOL}_{i,m} + \lambda_m^+ \text{RES}_{i,m}^+ + \lambda_m^- \text{RES}_{i,m}^- + \text{controls}_{i,m} + u_{i,m+1}, \quad (16)$$

For the purpose of this regression specification, we define the monthly idiosyncratic reversal effect to be *symmetric* if $\lambda_m^+ = \lambda_m^- < 0$. Our empirical results are instead consistent with a strong *asymmetry* in that $\lambda_m^+ \ll \lambda_m^-$. Our empirical findings are also consistent with $\lambda^{\text{IVOL}} = 0$. That is, after controlling for asymmetric idiosyncratic reversal, there is no evidence of an IVOL effect.

⁹Consistent with our estimation in Section 3, each cross-sectional regression uses WLS with market-equity weights winsorized to the 80th percentile of the NYSE distribution to limit excessive concentration.

However this very asymmetry—the empirical finding that positive residuals reverse so much more strongly than negative reversals at a monthly horizon—helps to explain why we observe an IVOL effect: the regression estimated in equation (15) shows that a security’s IVOL is (roughly) equal to $0.07 \times (\text{RES}^+ - \text{RES}^-)$, plus noise (η). If the premium per unit exposure at a monthly horizon is larger for RES^+ , then the RES^+ effect will dominate. That is, high IVOL securities will earn lower returns. However, once we control for RES^+ and RES^- , IVOL should earn no premium.

We examine these implications with a set of [Fama and MacBeth \(1973\)](#) regressions. We report the results in Table 2. Column 7 estimates the full specification, and columns 1–6 estimate the relationship when one or more of the independent variables are excluded from the estimation. Our controls are: market beta estimated over the previous 60 months; log size; log book-to-market; operating profitability; one-year asset growth; and prior 12-2 momentum ([Carhart, 1997](#)). We run these regressions using WLS, such that the coefficient estimates can be interpreted as the returns on zero-investment portfolios with unit exposure to that coefficient, zero exposure to all others.

Column 1 shows that idiosyncratic volatility remains strongly significant after accounting for return variation associated with a much broader set of economic characteristics beyond the market, size, and value. When we do not control for residual returns, the Newey–West t -statistic associated with IVOL is -5.28 . Note that we are calculating our residuals with a more comprehensive orthogonalization—specifically using daily cross-sectional regressions on the 151 characteristics plus 49 industries and dropping the three days around earnings announcements, as opposed to the FF3 time-series regression approach adopted by [Ang, Hodrick, Xing, and Zhang \(2006\)](#). The regression results in Column 1 confirm that IVOL calculated using these residuals remains strongly negatively related to excess returns in the following month.¹⁰

Columns 2 and 3 examine RES^+ and RES^- in isolation, and column 4 examines the joint significance. Both components show significant reversal effects, consistent with previous findings in Table 1. However, the coefficient and t -stat on RES^+ are far larger than the corresponding values for RES^- . Equality between the two slope coefficients is strongly rejected (Newey–West $t = -3.54$).

Columns 5 and 6 show that including IVOL and either RES^+ or RES^- results in large changes in the coefficient on both IVOL and the signed residuals. This is because of the strong correlations between IVOL and these signed residuals (see the estimated

¹⁰The fact that our characteristic-rich IVOL retains its ability to forecast the cross-section of returns is difficult to reconcile with explanations based only on missing systematic factors.

coefficients and t-stats in equation (15)). Finally, column 7 presents the full regression from equation (16), and shows that IVOL has no significant predictive power for future monthly returns after controlling for the signed residuals. Thus, these results are consistent with the hypothesis that the IVOL anomaly is not an independent effect, but rather a manifestation of the stronger asymmetric reversal effect.¹¹

Once the IVOL effect is read as a manifestation of AIR, its expected sign depends on the relative predictive power of RES^+ and RES^- . At a monthly frequency, the larger predictive effect of RES^+ dominates the contribution of RES^- , producing the negative IVOL–return relation documented in the literature. In Section 6, we show that this monthly asymmetry reflects the different speeds of reversal: negative residual shocks reverse more quickly, whereas positive residual shocks retain predictive content for longer. At shorter horizons, the contribution of RES^- should therefore dominate, implying a positive rather than negative IVOL relation.

Figure 2 examines this prediction. We repeat the FM regression in Column 1 of Table 2 but vary the measurement horizon of IVOL and future returns. For IVOL, we retain the demeaning and normalization in equation (14) and progressively include only the most recent H residuals in the sum, for $H = 1, \dots, 21$. We then estimate predictive FM regressions of returns measured over one-day, one-week, and one-month horizons on IVOL constructed in this way.

If the faster reversal of RES^- drives the short-horizon relation, the IVOL coefficient should gradually transition from negative to positive as we reduce the IVOL and return measurement horizons. Consistent with this prediction, IVOL forecasts *higher* returns the following day for H up to seven trading days. Increasing H and the return measurement horizon produce the familiar negative IVOL–return relationship. These findings further suggest that the IVOL effect arises because of AIR and it is not an independent phenomenon.

¹¹ A back-of-the-envelope calculation demonstrates the consistency of the coefficients across columns of Table 2 and the projection coefficients in equation (15). Consider a stock-month with IVOL one unit higher than another. Since RES^+ and RES^- have approximately symmetric distributions, a unit increase in IVOL on average will reflect roughly equal and opposite shifts in the two components: $\Delta RES^+ \approx -\Delta RES^-$. Under this assumption, $\Delta IVOL \approx [0.078 - (-0.067)] \Delta RES^+ = 0.145 \Delta RES^+$ (from equation (15) with $\Delta RES^- = -\Delta RES^+$), so $\Delta RES^+ \approx \frac{1}{0.145} \Delta IVOL = 6.9 \Delta IVOL$ and $\Delta RES^- \approx -6.9 \Delta IVOL$. Substituting into the column 4 Fama–MacBeth equation gives

$$\Delta E[R] = (-0.063)(6.9) + (-0.035)(-6.9) \approx -0.193,$$

close to the actual column 1 IVOL slope of -0.195 . Analogous calculations recover the IVOL and signed-component coefficients in columns 5 and 6.

The asymmetric reversal pattern and the IVOL spanning result in this section are not driven by the controls or by the weighting scheme. In the full specification of Table 2 (i.e., with the IVOL, RES^+ , and RES^- terms), without the six characteristic controls, the slope on RES^+ is -0.064 ($t = -8.66$) and the IVOL slope is 0.030 ($t = 0.72$), so IVOL remains insignificant once both signed components enter (Internet Appendix Table D.1). Replacing WLS with OLS leaves the asymmetry and the IVOL spanning intact: in the full OLS specification with controls, the slope on RES^+ is -0.064 ($t = -12.39$) and the IVOL slope is 0.005 ($t = 0.15$) (Internet Appendix Table D.2). Finally, the result does not reflect earnings-announcement contamination of the IVOL window: when we skip earnings-announcement windows in the construction of IVOL, we find that its coefficient remains below conventional significance levels in every column (Internet Appendix Table D.3).

5.3 Arbitrage asymmetry, mispricing, and AIR

Stambaugh et al. (2015) propose an alternative explanation for the IVOL anomaly based on “arbitrage asymmetry.” They contend that high-IVOL stocks are the riskiest to arbitrage (e.g., because of margin calls). As a result, mispricing is less likely to be corrected among high-IVOL stocks. Further, since mispricing is more likely to manifest itself in overpricing (because short-selling constraints lead stock prices to be biased toward optimists’ beliefs—Miller (1977)), they argue that IVOL should be a stronger predictor of negative future performance among overpriced stocks. They measure the degree of overpricing through a composite rank constructed from 11 anomalies, and they confirm that the IVOL anomaly is primarily present among highly overpriced stocks. Instead, our explanation for the IVOL anomaly is linked to the asymmetry in reversal, which we argue is likely due to the dynamics of liquidity provision, and thus not specific to one particular type of firm. To confront the two explanations, we sort stocks based on the mispricing index of Stambaugh et al. (2015) and confirm that IVOL is more prevalent among overpriced stocks, but show that AIR is present in each mispricing bucket and drives out the IVOL anomaly even among overpriced stocks. Thus, asymmetric arbitrage risk, as proxied by IVOL, has no incremental power to explain the cross-section of short-term returns once we control for AIR, even among the most overpriced stocks.

Specifically, we sort stocks each month into quintiles using their stock-level mispricing score, denoted MISPR, which ranges from zero for the most underpriced stocks

to 100 for the most overpriced stocks. Within each MISP quintile, we estimate monthly Fama–MacBeth regressions of next-month excess returns on IVOL, RES^+ , RES^- , and the same controls as in Table 2.¹² This design asks whether IVOL remains incremental to the signed residual components inside mispricing groups, including among overpriced stocks where the [Stambaugh et al. \(2015\)](#) mechanism predicts IVOL effects should be strongest.

Panel A of Table 3 shows that the MISP sort behaves as expected. The median mispricing score rises from 32.99 in the most underpriced portfolio to 67.07 in the most overpriced. Median IVOL rises from 24.43% to 32.27%, while median market equity falls from \$1.42 billion to \$0.61 billion. The signed residual components also become larger in absolute value as MISP increases: median RES^+ rises from 0.57% to 0.74%, and median RES^- falls from -0.58% to -0.75% . Thus the overpriced portfolio contains high-IVOL stocks and large residual shocks of both signs.

Panel B reproduces the key result of [Stambaugh et al. \(2015\)](#) in our extended sample. The IVOL premium is small and statistically insignificant within the portfolio of the most underpriced stocks (-0.020 , $t = -0.39$) and becomes increasingly negative for more overpriced securities, reaching -0.342 ($t = -6.11$) in the most overpriced portfolio. Panel C then shows that the two signed residual components carry return predictability within the same MISP portfolios. The coefficient on RES^+ is negative and highly significant in every portfolio, ranging from -0.055 ($t = -8.64$) among underpriced stocks to -0.076 ($t = -10.49$) among overpriced stocks. The coefficient on RES^- is also negative in every portfolio. This reversal effect is strongest in the underpriced portfolio (-0.063 , $t = -7.40$) and weakens toward the overpriced portfolio (-0.017 , $t = -1.76$).

Panel D asks whether IVOL contains incremental priced variation once we also control for RES^+ and RES^- . We find that it does not. The IVOL coefficient is economically small and statistically insignificant in every MISP portfolio, ranging from -0.084 to 0.137 in the interior portfolios and equaling 0.038 ($t = 0.40$) among overpriced stocks. The RES^+ slope remains negative and highly significant in all five portfolios, and the joint evidence shows that IVOL does not carry independent return predictability beyond its loading on RES^+ and RES^- . The apparent return predictability

¹²[Stambaugh et al. \(2015\)](#) use independent 5-by-5 sorts on IVOL and MISP in their baseline portfolio tests. We use conditional sorts on MISP instead. Since we are interested in the joint relationship between MISP, IVOL, RES^+ , and RES^- , unconditional sorts involving all four variables would result in sparse portfolio intersections. Conditional sorts allow us to study how these characteristics relate to returns for each level of MISP within appropriately diversified portfolios.

associated with IVOL in Panel B therefore reflects the changing balance between the two residual components as MISP increases: the predictive power of RES^- weakens, while RES^+ remains a strong negative predictor of future returns. As the positive return predictability associated with RES^- fades, IVOL increasingly reflects exposure to positive residual shocks, making the standalone IVOL effect appear stronger among overpriced stocks.

Interestingly, Panel D shows that there is an interaction between the strength of AIR and mispricing: RES^+ becomes progressively stronger, whereas RES^- becomes weaker, as we move from underpriced to overpriced stocks. We conjecture that this has to do with the economics of liquidity provision. Since it is much riskier to buy rather than sell an overpriced stock, it seems intuitive that liquidity providers would be less eager to provide liquidity to large unexpected sell orders and thus that reversal would be stronger following positive rather than negative residual shocks among overpriced stocks.

5.4 Concavity in AIR

The previous section established that including separately RES^+ and RES^- in a linear specification is sufficient to drive out IVOL. Note that both RES^+ and RES^- give equal weight to all daily residuals irrespective of their size and time within a month. In Section 6 we will explore the daily impulse response function of returns to signed daily residual shocks. In order to gain some intuition about possible non-linearities in the reversal response, in this section we explore the possibility of a concave relation between residual returns and future reversals.

Specifically, we focus on a simple proxy for residual concentration, which captures whether the total monthly sum of positive (or negative) residuals is concentrated in a few days or equally dispersed across several days. Our premise is that a higher concentration is likely to capture more informed trades, and thus less subsequent reversal. One rationale would be that information-related price changes tend to be larger than temporary price pressure moves ([Boudoukh et al., 2013](#); [French and Roll, 1986](#); [Chan, 2003](#); [Tetlock, 2011](#)).

We measure the residual concentration of positive and negative residuals, denoted by $\text{CONC}^{+,-}$ as follows:

$$\text{CONC}_{i,m}^+ = \frac{\sqrt{\sum_{t \in \mathcal{D}_{i,m}} (\tilde{\varepsilon}_{i,t}^+)^2}}{\text{RES}_{i,m}^+}, \quad (17)$$

$$\text{CONC}_{i,m}^- = \frac{\sqrt{\sum_{t \in \mathcal{D}_{i,m}} (\tilde{\varepsilon}_{i,t}^-)^2}}{\text{RES}_{i,m}^-}. \quad (18)$$

We set $\text{CONC}_{i,m}^k$ to zero when $\text{RES}_{i,m}^k = 0$. Because RES^- is negative, CONC^- is also negative. In absolute value, CONC^k is the square root of a Herfindahl index computed from each day's share of RES^k . A larger absolute value therefore means that RES^k is more concentrated in a few daily shocks. It equals one when the entire signed component occurs on a single day and decreases as RES^k is spread more evenly across days.

The normalization by RES^k separates concentration from the scale of residual returns. The numerator is the square root of the sum of squared sign-specific residuals and, without the normalization, would primarily identify stocks with high residual volatility. Dividing by the corresponding signed residual sum instead measures concentration for a given monthly residual component. CONC can therefore distinguish two stock-months with the same RES^+ or RES^- but different exposure to extreme daily shocks.

Table 4 tests whether RES^+ and RES^- are followed by less reversal when they are concentrated in a few daily shocks. Column 1 reports the baseline regression with RES^+ and RES^- . Column 2 adds the two signed concentration measures. Both concentration coefficients are positive and statistically significant. A positive coefficient on CONC^+ offsets part of the negative coefficient on RES^+ : greater concentration of RES^+ is associated with less subsequent reversal. Because CONC^- is negative, its positive coefficient has the corresponding interpretation for RES^- . Greater concentration makes CONC^- more negative and is associated with a smaller subsequent rebound. Thus, both RES^+ and RES^- are followed by less reversal when concentrated, as predicted. The equality of the two concentration coefficients is not rejected in Column 2 (Newey–West $t = -1.52$).

Column 3 shows that both concentration coefficients remain positive and statistically significant after we also control for the systematic return component. Their

equality is again not rejected (Newey–West $t = -1.84$). Thus, we cannot reject symmetry in the association between concentration and subsequent reversal across positive and negative shocks. As with IVOL, the numerators of both concentration measures are square roots of sums of squared residuals and are therefore nonnegative. Whenever both signed residual components are nonzero, their denominators, RES^+ and RES^- , have opposite signs, and so do $CONC^+$ and $CONC^-$; conditional on the signed residual components, equal slopes therefore imply that their return-predictive contributions enter with opposite signs and partially offset. Column 4 imposes equality of the two coefficients. Under this restriction, the signed concentration measures enter the regression through their sum, $CONC = CONC^+ + CONC^-$. The single measure therefore captures the common predictive relation across signs and is the regressor implied by the common-coefficient restriction. Its coefficient is positive and highly statistically significant.

Together, these results support a concave relation between the initial residual displacement and subsequent reversal.

5.5 Spanning the short-term zoo with AIR

The results in the previous section show that signed idiosyncratic reversal factors subsume the [Ang et al. \(2006\)](#) IVOL factor in explaining the cross-section of monthly returns. However, since the initial reversal studies ([Jegadeesh, 1990](#); [Lehmann, 1990](#)) and the [Ang et al. \(2006\)](#) IVOL study, numerous other characteristics have been shown to have power to forecast the cross-section of monthly returns.

In this section, we examine the extent to which our signed idiosyncratic reversal factors subsume thirteen additional characteristics from this literature that measure short-horizon return magnitudes, return tails, liquidity, trading costs, and trading activity.

We find that none of the thirteen characteristics is significant with its previously documented sign once we control for RES^+ and RES^- . Table 5 summarizes the construction, predicted signs, and reference papers for the thirteen characteristics.

We group the short-term characteristics into three groups. The first group parallels our comprehensive IVOL measure, developed in Section 5.1, and includes both the FF3-based idiosyncratic volatility and total return volatility measures utilized by [Ang et al. \(2006\)](#).

The second group comprises characteristics designed to capture investor preferences for lottery-like stocks ([Barberis and Huang, 2008](#); [Mitton and Vorkink, 2007](#); [Boyer et al., 2010](#); [Bali et al., 2011, 2017](#); [Asness et al., 2020](#)). The common thread motivating these characteristics is the idea that some investors overweight small probabilities of large gains. Stocks with lottery-like payoffs can therefore become overpriced and earn low subsequent returns. In these theories, short-horizon return tails matter because they capture payoff asymmetry and extreme positive returns, the same features that also make lottery-like stocks volatile. We use six proxies: daily return skewness, FF3 idiosyncratic skewness, one-month CAPM residual coskewness, the maximum daily return over the formation month (MAX), the average of the five largest daily returns (MAX5), and scaled-MAX (SMAX), defined as MAX5 divided by trailing daily return volatility.

The third group of characteristics is motivated by the idea that liquidity is priced. Lagged returns are linked to temporary price pressure and therefore to the liquidity-provision view of short-term reversal ([Lehmann, 1990](#); [Jegadeesh, 1990](#); [Lo and MacKinlay, 1990](#); [Nagel, 2012](#); [Da et al., 2014](#); [Blitz et al., 2013](#)). The other variables capture different margins of low liquidity, motivated by the hypothesis that investors require compensation to hold illiquid stocks. We use the prior-month return (Lag Ret), the [Amihud \(2002\)](#) illiquidity measure, the number of zero-trading days ([Lesmond et al., 1999](#); [Liu, 2006](#)), and an effective bid-ask spread estimate based on [Corwin and Schultz \(2012\)](#) (Spread) ([Amihud and Mendelson, 1986](#); [Corwin and Schultz, 2012](#)). We also include average daily share turnover over the previous month because the relationship between turnover and returns received significant attention in the literature. Using turnover measures at different horizons, [Datar et al. \(1998\)](#), [Lee and Swaminathan \(2000\)](#), and [Chordia et al. \(2001\)](#) find that high-turnover stocks earn lower subsequent returns.¹³

To align the timing with the residual-reversal measures in the rest of the paper, we compute each characteristic over one month of daily data excluding the last daily observation in the formation month. Internet Appendix Figure E.1 shows how this one-day skip affects the standalone return-predictability of each characteristic. Appendix E describes the construction of each variable in more detail. Several of these

¹³In partial contrast with these results, [Gervais et al. \(2001\)](#) study abnormal trading volume and find a high-volume return premium over the following month. [Medhat and Schmeling \(2022\)](#) report that one-month turnover does not have a statistically significant unconditional relation with next-month returns in their specification.

characteristics also appear in the JKP data, and Internet Appendix Table E.1 reports replication statistics for the non-skipped versions.

Panel A of Table 6 presents results from Fama–MacBeth regressions of each characteristic on RES^+ and RES^- . The coefficients and average R^2_{adj} highlight that several short-term characteristics are highly correlated with average monthly signed residuals. Explanatory power is highest for characteristics built directly from recent return magnitudes: roughly 50–70% for FF3 IVOL, return volatility, MAX, MAX5, and Lag Ret, and about 25% for SMAX. The fit is also meaningful for the effective-spread estimate and turnover, but much lower for skewness, coskewness, Amihud illiquidity, and zero-trading days. Thus, the signed residual components share the most content with characteristics that summarize recent price pressure, extreme returns, and short-horizon trading conditions. For volatility, extreme-return, spread, and turnover measures, the coefficients are consistent with average residual shocks of either sign being associated with higher characteristic values. In contrast, Lag Ret and the skewness measures preserve the direction of the underlying shock: positive residual shocks are associated with higher values, while negative residual shocks are associated with lower values.

Panels B to E estimate predictive Fama–MacBeth regressions of month $m + 1$ security returns on characteristics at the end of month m . Panel B reports standalone Fama–MacBeth slopes for each characteristic. Seven characteristics are statistically significant with their predicted signs, while Spread is significant with a negative sign, opposite to the prediction of [Amihud and Mendelson \(1986\)](#). The Skew, FF3 idiosyncratic skewness, Coskew, Amihud, and Zero-trade characteristics are statistically insignificant in this sample period. [McLean and Pontiff \(2016\)](#) document that anomaly returns decay after publication, and Panel B is consistent with that finding for the post-1972 cross-section.¹⁴

Panel C adds RES^+ and RES^- to each standalone specification, and four patterns emerge. First, the volatility variables are no longer statistically significant; AIR absorbs the cross-sectional variation that these characteristics capture. Second, MAX, MAX5, SMAX, and Lag Ret, all of which have a negative sign in the standalone regressions, have a positive and statistically significant coefficient after controlling for AIR. Third, the Coskew, Amihud, Zero Trades, Spread, and Turnover characteristics are all insignificant after the residual controls. Finally, we note that, across all 13 columns, the

¹⁴In additional unreported tests, we find CAPM and [Hou et al. \(2015\)](#) q-factor variants of idiosyncratic volatility and idiosyncratic skewness give qualitatively and quantitatively similar spanning results.

RES^+ and RES^- coefficients remain large and highly statistically significant, and the asymmetry between the two signed components survives every spanning specification.

Panel D augments RES^+ and RES^- with CONC to account for the concavity in AIR. The coefficient on CONC is positive and highly statistically significant in every column, consistent with less reversal when RES^+ and RES^- are concentrated in a few daily shocks. Including CONC reduces the t-statistics on the thirteen characteristics but it does not eliminate their statistical significance.

Panel E further adds SYS. With both the concavity in AIR and the systematic component included, none of the thirteen characteristic coefficients remains statistically significant. In particular, variations of skewness and MAX, which remain significant after CONC enters in Panel D, fall below conventional significance levels once SYS is also included. By contrast, RES^+ , RES^- , CONC, and SYS remain statistically significant across specifications.

Overall, the spanning tests identify three relevant features of recent returns: the sign and magnitude of residual price pressure, captured by RES^+ and RES^- ; systematic continuation, captured by SYS; and the concentration of firm-specific shocks, captured by CONC. Once we control for these three features, none of the thirteen short-term characteristics has independent predictive power. The evidence therefore points to a common short-horizon return-decomposition mechanism rather than a set of separate one-month anomaly explanations.

Lastly, we note that several characteristics are not significant in the standalone regressions in Panel B of Table 6. This is unsurprising given the empirical design. The regressions include the six FF6 controls and extend through 2022, whereas many original studies use shorter samples and predate the now-standard FF6 benchmark. McLean and Pontiff (2016) show that anomaly returns tend to decay after publication, so Internet Appendix Table E.2 re-estimates the spanning specifications over characteristic-specific reference windows. The full-sample results carry over. None of the thirteen characteristics is significant with its predicted sign once we control for RES^+ and RES^- .

5.6 Additional robustness tests

Internet Appendix Table D.4 asks whether the monthly sign asymmetry is already present in raw returns. We split each stock-month's raw return into positive-day and negative-day contributions, using the same one-day skip and earnings-announcement-window exclusion as in the signed residual measures. The raw-return-only regressions show an asymmetric reversal pattern, but this pattern disappears once RES^+ and RES^- enter the regression. The signed residual components remain strongly negative, and the $RES^+ - RES^-$ difference is significant in the controlled WLS specification and in both OLS specifications. Thus, the raw-return reversal asymmetry operates through the residual component of returns.

6 Understanding AIR

The analysis in the previous section demonstrates that signed residuals are asymmetric: at a monthly horizon positive residuals have greater power to forecast future returns than do negative residuals. We now examine the high-frequency dynamics that are responsible for this asymmetry. We examine the impulse responses to idiosyncratic and systematic shocks, as defined earlier. We establish three patterns:

1. A substantial fraction (about 20%) of residual shocks is temporary, and reverses over 1-2 months. At horizons of multiple months, residuals exhibit continuation or momentum. Systematic shocks exhibit little reversal and, beyond one month, mostly momentum.
2. The half-lives of the residual impulse responses are strongly asymmetric. Positive shocks reverse slowly, negative shocks quickly. The impulse response to systematic shocks is largely symmetric.
3. Roughly the same fraction of a 1% residual shock is temporary irrespective of its sign, but this temporary pressure dissipates faster after negative shocks.

As we discuss below, these results suggest a link between the asymmetry and the dynamics of liquidity provision.

These asymmetries are consistent with the monthly patterns documented in the previous section. Negative idiosyncratic shocks reverse over a span of a few days,

and positive shocks over multiple weeks. As a result, RES^- does not do as good a job at forecasting the return over the coming month; on average, most of the temporary component has already decayed away. As we showed in the previous section, this differential leads to the IVOL effect.

6.1 Daily impulse responses

For each firm on each trading day, we decompose the firm's return into systematic and residual components ($\tilde{r}_{i,t}$ and $\tilde{\varepsilon}_{i,t}$) exactly as described in Section 3. We denote by $\tilde{\varepsilon}_{i,t}^+ = \max\{\tilde{\varepsilon}_{i,t}; 0\}$ and $\tilde{\varepsilon}_{i,t}^- = \min\{\tilde{\varepsilon}_{i,t}; 0\}$ the positive and negative parts of firm i 's residual returns on day t . We apply the same decomposition to the systematic component, producing $\tilde{r}_{i,t}^+$ and $\tilde{r}_{i,t}^-$.

We then run cross-sectional (Fama–MacBeth) regressions of firms' daily excess returns on 252 lags of these four signed components:

$$r_{i,t} = \lambda_t^0 + \sum_{\tau=1}^{252} \left[\lambda_{\tau,t}^{\varepsilon,+} \tilde{\varepsilon}_{i,t-\tau}^+ + \lambda_{\tau,t}^{\varepsilon,-} \tilde{\varepsilon}_{i,t-\tau}^- + \lambda_{\tau,t}^{r,+} \tilde{r}_{i,t-\tau}^+ + \lambda_{\tau,t}^{r,-} \tilde{r}_{i,t-\tau}^- \right] + u_{i,t}. \quad (19)$$

The four coefficients obtained through each cross-sectional regression in (19) are the day t returns on zero-cost portfolios with unit exposure to a particular return component (systematic or idiosyncratic), sign (positive or negative), and lag (1 to 252). Each portfolio is orthogonal to all remaining components at all lags. The time-series averages of these coefficients, $\lambda_{\tau}^{\varepsilon,+}$, $\lambda_{\tau}^{\varepsilon,-}$, $\lambda_{\tau}^{r,+}$, and $\lambda_{\tau}^{r,-}$, are estimators of the expected returns associated with unit shocks to each component τ days before, holding everything else constant.

We interpret these average coefficients as estimates of the return premium associated with liquidity provision. To the extent that the characteristics and industries in the regression in equation (3) capture all of the fundamental information that drives stock prices, the positive and negative residuals $\tilde{\varepsilon}_{i,t-\tau}^+$ and $\tilde{\varepsilon}_{i,t-\tau}^-$ will be the result of orders orthogonal to this public information. These orders can therefore either reflect (uninformed) demand for liquidity, or trading in response to private information. High-frequency liquidity providers take the other side of these trades in exchange for a price concession. The returns following these shocks are therefore informative about the compensation embedded in prices for supplying immediacy, and compensate the liquidity providers for inventory risk, and for execution costs.

To see the construction, consider a realization of $\tilde{\varepsilon}_{i,t-1}^+$. In the cross-section at time t , the lag-one Fama–MacBeth portfolio has unit exposure to this lagged component and zero exposure to the other component-lag regressors, so its realized return is $\hat{\lambda}_{1,t}^{\varepsilon,+}$ per unit of the lagged shock. One day later, the same original realization enters the regression as a lag-two component; the corresponding mimicking-portfolio return is $\hat{\lambda}_{2,t+1}^{\varepsilon,+}$. Iterating this construction gives the sequence of returns associated with the original shock, net of later shocks and net of the other return components.

For residual shocks, this tracked return response connects to liquidity provision. The impulse response measures the return path associated with the original residual displacement after subsequent shocks and other return components are sterilized. We therefore scale the mimicking-portfolio returns by a signed one-percent shock, anchor the response at +1% for positive components and -1% for negative components, and interpret liquidity-provider gross revenue for residual shocks as the distance back from this signed event-time anchor.

$$\text{IR}_t^{\varepsilon^+}(\tau) = (1 + 0.01) \prod_{h=1}^{\tau} (1 + 0.01 \hat{\lambda}_{h,t+h}^{\varepsilon,+}) - 1, \quad \tau = 1, \dots, 252, \quad (20)$$

where $\hat{\lambda}_{h,t+h}^{\varepsilon,+}$ is the lag- h mimicking-portfolio return estimated from the cross-sectional regression at calendar time $t + h$.

At event time zero, the path is anchored at +1%. We define the response for $\tilde{\varepsilon}^-$, $\tilde{r}^+$, and $\tilde{r}^-$ analogously, replacing the coefficient path and using a +1% anchor for positive-sign components and a -1% anchor for negative-sign components. Equation (20) gives the compounded event-time return response implied by the sequence of Fama–MacBeth mimicking-portfolio returns. The corresponding gross liquidity-provision revenue at horizon τ is $1\% - \text{IR}^{\varepsilon^+}(\tau)$ after a positive residual shock and $\text{IR}^{\varepsilon^-}(\tau) + 1\%$ after a negative residual shock. The positive-residual impulse-response function is the time-series average,

$$\text{IR}^{\varepsilon^+}(\tau) = \frac{1}{T} \sum_{t=1}^T \text{IR}_t^{\varepsilon^+}(\tau), \quad (21)$$

with Newey–West standard errors from the time series $\{\text{IR}_t^{\varepsilon^+}(\tau)\}_{t=1}^T$ to account for any serial correlation in the time series of FM coefficients. This average is the expected cumulative return on the dynamic sequence of mimicking portfolios that tracks the

initial component shock through event time. The impulse response for the other three components is calculated similarly.

6.2 Temporary and persistent components of residual shocks

Figure 3 plots $IR(\tau)$, and 95% confidence intervals, for all four components. For residual shocks, the IR plot illustrates that about a fifth of the initial $\pm 1\%$ shock is temporary for both the positive and negative shock: following a -1% residual shock, the price on average moves up by about 21 bps (to -0.79%) over the next 1.5 months. Following a $+1\%$ shock, the price falls by about 19 bps (to 0.81%) after roughly two-and-a-half months. Figure 4 zooms in on the first 120 trading days of the two residual impulse responses.

Following this “reversal” phase, the price starts a *continuation* or *momentum* phase, moving in the same direction as the initial shock and continues for a little less than a year (252 trading days). Again, the magnitude of the continuation is approximately the same for the positive and negative shocks (9 bps and 12 bps, respectively).

For comparison, the systematic components $\tilde{r}^+$ and $\tilde{r}^-$ exhibit almost no reversal, and stronger momentum. Following a 1% shock to either systematic component, the return response drifts in the same direction over the following year, consistent with momentum: $\tilde{r}^+$ reaches about $+1.1\%$ and $\tilde{r}^-$ reaches about -1.2% . Both systematic-component paths deviate from monotone momentum at short horizons.

Following a $+1\%$ $\tilde{r}^+$ shock, the IR initially falls by 3 bps (to 0.97%) over the next 12 trading days, but then rises by 16 bps over the remainder of the year following the shock. For the -1% $\tilde{r}^-$ shock, the initial reversal (price rise) is 5 bps over the first three weeks (14 trading days), but then the price falls by 25 bps over the remainder of the year.

Consistent with the industry-momentum evidence in Moskowitz and Grinblatt (1999), most of the continuation in our decomposition appears in the systematic component, which includes industry portfolios and characteristic-based factor portfolios. The residual paths therefore suggest that stock-specific residual momentum is a second-order effect. After removing a broad systematic component, the average residual shock still contains a smaller continuation component. This residual persistence connects to evidence on stock-specific and residual momentum in Grundy and Martin (2001) and Blitz et al. (2011). Our contribution in this section is to trace the daily

dynamics behind this distinction: residual reversal dominates early, but the average residual response switches toward continuation at medium horizons.

6.3 Reversal speed and sign asymmetry

Figure 5 quantifies the reversal asymmetry directly by plotting $IR^{\varepsilon^+}(\tau) + IR^{\varepsilon^-}(\tau)$. Intuitively, this sum tracks the compensation of the liquidity provider when she accommodates both a positive and a negative 1% residual shock on two baskets of securities. The sum is zero when the two components are mirror images. A positive sum indicates that cumulative negative-shock reversal dominates positive-shock reversal at horizon τ . The sum rises over the first trading week and then declines toward zero, remaining positive through roughly two months. This pattern confirms that $\tilde{\varepsilon}^-$ reverts faster at short horizons. During the first trading week, the average reversal coefficient for $\tilde{\varepsilon}^-$ is approximately twice that for $\tilde{\varepsilon}^+$. The ratio converges to unity after about two months. The asymmetry is established within the first trading week and subsequently attenuates.

The evidence points to asymmetry in *speed*, not to a large difference in total reversal *quantity*. The residual extrema are similar in economic magnitude: about 19 bps of reversal after a positive residual shock and about 21 bps after a negative residual shock. What differs is when that reversal arrives. Negative residual shocks move back toward zero more quickly, while positive residual shocks reverse more slowly.

The analogous sum for systematic components shows no monotone pattern: the systematic IR-difference fluctuates irregularly and is generally statistically indistinguishable from zero. Because systematic-component dynamics are sign-symmetric, we pool $\tilde{r}^+$ and $\tilde{r}^-$ into a single systematic component $\tilde{r} = \tilde{r}^+ + \tilde{r}^-$ in the remainder of our analysis.

6.4 Spline summary and monthly aggregation

The dense specification (19) estimates 1,008 free slope coefficients per cross-section. The large parameter count reduces statistical power and generates noisy lag-by-lag coefficient estimates that obscure the underlying smooth lag structure, particularly at medium and long horizons. We address this by restricting the coefficient sequences to lie in the column space of a degree-1 spline basis of dimension $K = 27$. Beyond

dimensionality reduction, the spline is appealing because it preserves smooth local decay, consistent with the shape of the impulse responses in Figure 3.

Let $\mathbf{B}(\tau) = (B_1(\tau), \dots, B_K(\tau))'$ denote the vector of degree-1 basis functions evaluated at lag τ . The spline specification replaces the unrestricted lag-level coefficients in (19) with restricted Fama–MacBeth coefficients that are smooth functions of lag. Because systematic-component dynamics are sign-symmetric, we pool $\tilde{r}^+$ and $\tilde{r}^-$ into the full signed systematic component $\tilde{r}$ in the spline regression. The restricted regression is

$$r_{i,t} = \lambda_t^0 + \sum_{\tau=1}^{252} \left[\sum_s \underbrace{\mathbf{B}(\tau)' \gamma_t^{\varepsilon,s}}_{\lambda_{\tau,t}^{\varepsilon,s}} \tilde{\varepsilon}_{i,t-\tau}^s + \underbrace{\mathbf{B}(\tau)' \gamma_t^r}_{\lambda_{\tau,t}^r} \tilde{r}_{i,t-\tau} \right] + u_{i,t}. \quad (22)$$

The objects below the braces are the implied lag-level Fama–MacBeth coefficients. Only the low-dimensional vectors $\gamma_t^{\varepsilon,+}$, $\gamma_t^{\varepsilon,-}$, and γ_t^r are estimated. Equivalently, define the spline-projected lag vectors

$$\mathbf{g}_{i,t-1}^{\varepsilon,s} = \sum_{\tau=1}^{252} \mathbf{B}(\tau) \tilde{\varepsilon}_{i,t-\tau}^s, \quad \mathbf{g}_{i,t-1}^r = \sum_{\tau=1}^{252} \mathbf{B}(\tau) \tilde{r}_{i,t-\tau}. \quad (23)$$

The subscript $t-1$ records that each projected vector uses lagged information through day $t-1$ when the dependent return is $r_{i,t}$. The same spline Fama–MacBeth regression can therefore be estimated as

$$r_{i,t} = \lambda_t^0 + \sum_s (\mathbf{g}_{i,t-1}^{\varepsilon,s})' \gamma_t^{\varepsilon,s} + (\mathbf{g}_{i,t-1}^r)' \gamma_t^r + u_{i,t}, \quad (24)$$

Equation (24) preserves the Fama–MacBeth mimicking-portfolio interpretation, but the unit-exposure object is now a return component over an event-time region rather than a single lag. For example, one basis portfolio isolates exposure to positive residual shocks from the first trading day after the shock, while another isolates exposure to shocks from a later trading week or month. The estimated basis loading is therefore the return to a portfolio exposed to that part of the reversal-or-momentum path, controlling for the other residual and systematic lag regions.

The first five basis functions represent individual trading days, the next twelve represent successive trading weeks, and the final nine represent successive trading months, with a final anchor at the one-year horizon. This timing reflects the economics of the return response. Liquidity-driven reversal is concentrated in the first

days and weeks after the shock, so we let the data distinguish those early horizons finely. Momentum and residual persistence evolve more gradually at longer horizons, so weekly and monthly basis portfolios are sufficient to capture their contribution. The cost is that the classic unit-exposure interpretation for each individual lag becomes approximate: the implied lag-level coefficient is the smooth value $B(\tau)' \gamma_t$, while the estimated coefficients are the lower-dimensional basis loadings γ_t . The spline regression has 81 free slope parameters rather than over 1,000, a reduction by a factor of 12 without imposing a parametric functional form.

Figure A.5 illustrates the knot placement and the shape of representative basis functions. Each degree-1 basis function is a tent function localized over two consecutive intervals between knots, and the 27 functions form a partition of unity over the lag grid. The varying knot density (daily, weekly, and monthly) is visible in the timeline schematic.

Figure 6 overlays the impulse-response functions reconstructed from the spline specification on the dense FM estimates. For all component-sign paths, the spline IR closely tracks the dense estimate, confirming that the smoothness restriction does not materially distort the economically relevant dynamics. The main departures are in the early lags of the systematic component, where using the full $\tilde{r}$ rather than its positive and negative parts separately produces a somewhat smoother trajectory. The residual paths are virtually identical between the two specifications, and the reversal-to-momentum switching points, around one-and-a-half and two-and-a-half months, are preserved. Precision gains are substantial: the 95% confidence bands for the spline IR are noticeably narrower than those of the dense specification, particularly at horizons beyond one month, where the dense regression suffers from the highest multicollinearity.

The monthly evidence aggregates these daily dynamics unevenly across horizons. The signed monthly residuals in equations (12) and (13) are the positive and negative residual contributions to the monthly residual sum. Abstracting from compounding, the next-month return is the sum of daily returns during the holding month. A monthly regression therefore maps the daily impulse-response estimates into the monthly slope by counting how many formation-month residuals are paired with holding-month returns at each event-time distance.

The shape of these counts is easiest to see in a 21-day month, abstracting from the one-day skip. If one regresses next-month returns on previous-month residual returns, only one holding-period return has a formation-month residual at lag 1, only

two have such residuals at lag 2, and so on, until all holding-period returns have a formation-month residual at lag 21. The counts then fall symmetrically at longer distances. One-month regressions therefore place little weight on the most recent daily lags and the largest weight near the middle of the formation-to-holding overlap. Internet Appendix C derives the corresponding aggregation weights assuming a 20-day formation window, one skipped trading day, and a 21-day holding window.

Figure 7 is the empirical counterpart of this aggregation. The top panel reports spline-implied residual return responses by horizon block for a 1% absolute shock to $\tilde{\varepsilon}^+$ (red bars) and $\tilde{\varepsilon}^-$ (blue bars), with 95% Newey–West confidence intervals. For example, a daily block is the expected return response over that trading-day horizon after a 1% residual shock. A weekly block is the cumulative expected return response over the trading days in that weekly horizon block after the same shock. Negative bars indicate movement back toward zero for both positive and negative residual shocks, and therefore indicate reversal. The first daily bins show a larger reversal response after negative residual shocks. In later bins, the negative-shock reversal differential narrows and can tilt toward stronger positive-shock reversal, even though the cumulative daily IR asymmetry remains positive for several weeks because of the large initial negative-shock response.

The bottom panel overlays this marginal sign asymmetry with the normalized triangular weights implied by the monthly construction. Positive values of the line indicate stronger reversal after negative residual shocks, while negative values indicate stronger reversal after positive residual shocks. The gray bars show that the monthly weights are largest around lags 16 to 25, after the first-week negative-shock reversal differential has largely dissipated. This aggregation reconciles the daily and monthly evidence. The one-month regressions in Table 2 put limited weight on the initial speed differential in negative-shock reversal and more weight on lags near the middle of the daily-lag aggregation window. The stronger monthly slope on RES^+ therefore reflects timing and aggregation, rather than a contradiction in the daily impulse responses.

7 A residual return factor

The evidence above shows that the monthly residual measure RES in equation (10) is a coarse proxy for the return component associated with residual shocks. It combines positive and negative residuals without distinguishing their signs, even though their

impulse responses differ. It also gives the same weight to every residual in the formation month, even though the daily estimates show that residual reversal is concentrated at short horizons and that older residual shocks can carry residual momentum. We therefore construct a residual return factor that uses the estimated daily impulse responses by sign and lag to forecast which residual shocks should continue to predict returns at portfolio formation.

The construction starts from the spline regression in the previous section. We use a one-day-skipped analogue of the same decomposition-based spline structure as an out-of-sample forecasting device. Recall that s indexes the residual sign and takes values $\{+, -\}$. Let $R_{i,t}^{21}$ denote stock i 's excess return over the 21-trading-day holding interval that begins on trading day t . The dense Fama–MacBeth forecast regression is

$$R_{i,t}^{21} = a_t + \sum_{\tau=2}^{252} \left[\sum_s \lambda_{\tau,t}^{\varepsilon,s} \tilde{\varepsilon}_{i,t-\tau}^s + \lambda_{\tau,t}^r \tilde{r}_{i,t-\tau} \right] + u_{i,t}. \quad (25)$$

The first included lag is $\tau = 2$ because the forecast skips one trading day between the lagged return components and the holding period. We estimate (25) using the spline approximation in equation (22), rather than estimating each lag coefficient separately. For each portfolio-formation month m , we use only Fama–MacBeth coefficient estimates dated no later than the end of month $m - 1$, and take their expanding-window average. This timing makes the signal implementable out of sample: both the lagged residuals and the coefficients used to weight them are known before the holding month begins. We begin evaluating factor returns in January 1974, using the first two sample years to form more stable expanding-window coefficient averages before turning the forecast into a traded portfolio.

For a portfolio formed at the end of month m , let t_m denote the first trading day of the holding month. Let $\bar{\lambda}_{\tau,m}^{\varepsilon,s}$ denote the expanding-window average of the spline-implied residual coefficient for sign s and lag τ available at portfolio formation. Although equation (25) includes lagged systematic shocks as controls, the traded score uses only the fitted component associated with residual shocks. The full residual fitted value is

$$\hat{\mu}_{i,m}^{\varepsilon,\text{full}} = \sum_{\tau=2}^{252} \sum_s \bar{\lambda}_{\tau,m}^{\varepsilon,s} \tilde{\varepsilon}_{i,t_m-\tau}^s. \quad (26)$$

The corresponding one-month residual fitted value uses only the first 21 admissible lags,

$$\hat{\mu}_{i,m}^{\varepsilon,21} = \sum_{\tau=2}^{22} \sum_s \bar{\lambda}_{\tau,m}^{\varepsilon,s} \tilde{\varepsilon}_{i,t_m-\tau}^s. \quad (27)$$

The asymmetric residual return (ASRES) score is

$$\text{ASRES}_{i,m} = \hat{\mu}_{i,m}^{\varepsilon,21} + 0.40 \left(\hat{\mu}_{i,m}^{\varepsilon,\text{full}} - \hat{\mu}_{i,m}^{\varepsilon,21} \right). \quad (28)$$

Equation (28) is deliberately simple. It gives full weight to the first 21 admissible lags, where short-term residual reversal is strongest, and gives 40 percent weight to the remaining fitted residual component. The long-lag term allows older residual shocks to contribute when the daily forecast assigns them predictive content, including the residual momentum documented above, while keeping the core short-term reversal period at the center of the signal.

Table 7 compares ASRES with standard reversal sorts. STREV sorts low-minus-high on one-day-skipped prior-month raw returns. The three RES columns sort low-minus-high on one-day-skipped residual returns from progressively richer return decompositions. ASRES is different because it is already a forecasted residual return: it sorts high-minus-low on the out-of-sample spline forecast in equation (28), so all columns have the same economic sign.

Panel A shows a clear performance ranking. The standard short-term reversal factor earns 0.26 percent per month, with a Newey–West t -statistic of 1.80. Residual return sorts perform much better: the three RES portfolios earn 0.88, 0.95, and 1.07 percent per month as the residual decomposition becomes richer. ASRES performs best. It earns 1.18 percent per month with a t -statistic of 10.56, has an annualized Sharpe ratio of 2.55, and earns a 0.98 percent monthly alpha after controlling for FF6 and the conventional reversal factor REV. The evidence indicates that the daily spline forecast adds information beyond the one-month residual sort. It combines the short-run residual reversal component with the longer-run residual momentum component that remains useful at portfolio formation.

Panel B reports the loadings from the FF6 plus REV alpha regression for ASRES. The market loading is small and statistically insignificant, and the investment loading is also insignificant. ASRES does load significantly on SMB, HML, RMW, UMD, and especially REV. The positive loading on REV confirms that ASRES is related to con-

ventional short-term reversal, as it should be. The large remaining alpha shows that conventional reversal and the standard factors do not span the residual return forecast.

Table 9 examines whether ASRES is concentrated in a narrow part of the sample. We form ASRES separately within monthly NYSE market-equity groups. The investable-size screen removes Nano stocks, so the reported groups are Micro, Small, Large, and Mega. ASRES is positive and statistically significant in every size group. Average excess returns range from 0.89 percent per month among mega caps to 1.43 percent among small stocks, and the FF6 plus reversal alphas range from 0.73 percent to 1.25 percent per month. The premium is therefore not only a microcap effect.

The final two columns split the sample around decimalization. We use April 2001 as the first post-decimalization month, following full decimalization on April 9, 2001; observations through March 2001 are pre-decimalization. ASRES is stronger before decimalization, with an average excess return of 1.65 percent per month, but remains economically large afterward, earning 0.60 percent per month with a t -statistic of 6.38. The post-decimalization FF6 plus reversal alpha is 0.51 percent per month. This subsample pattern is consistent with lower trading frictions weakening, but not eliminating, compensation for residual return reversal.

8 Conclusion

This paper shows that short-term reversal is not a property of past returns as a whole. It is concentrated in the residual component of returns after removing systematic variation associated with characteristics and industries. The same one-month return can therefore contain two opposing forces: residual shocks that partially reverse and systematic return components that continue. This distinction helps explain why standard short-term reversal sorts remain profitable even though short-horizon momentum is present in the cross-section.

We find a significant asymmetry in idiosyncratic residual returns (AIR). Negative residual shocks reverse faster than positive residual shocks, although the total reversal over longer horizons is similar for the two signs. At the monthly frequency, this difference in timing interacts with the aggregation weights embedded in one-month formation and holding periods, producing stronger return predictability from positive residual shocks. AIR subsumes the idiosyncratic-volatility anomaly and a broad

set of proposed explanations for it, suggesting that these characteristics partly proxy for recent residual return pressure.

An asymmetric idiosyncratic return reversal factor (ASRES), incorporating AIR using the estimated daily impulse responses by sign and lag, performs substantially better than standard reversal and simple idiosyncratic return sorts. Indeed, that factor has a Sharpe ratio of 2.55, more than twice the best-performing factor in the [Jensen et al. \(2023\)](#) database.

What could explain AIR? In a companion paper we develop a theoretical framework based on liquidity provision, learning about fire-sale risk, and slow-moving capital that generates this asymmetry. In our theory, the economic rationale for the asymmetry is that negative residual shocks are more likely to reflect a mixture of information and temporary liquidity-driven selling. When market participants observe a large negative idiosyncratic price movement, they are initially uncertain whether it reflects adverse information or non-informational selling pressure arising from fire-sales (such as redemptions, leverage constraints, or funding shocks). As this uncertainty is resolved over time and liquidity imbalances are absorbed by slower-moving investors, prices recover more rapidly. Positive residual shocks are less naturally associated with analogous fire-sale dynamics and therefore reverse more gradually.

More broadly, we expect AIR to be a general feature of equity markets rather than a phenomenon unique to the United States. The underlying mechanisms—temporary liquidity shocks, constrained intermediaries, and gradual risk transfer to slower-moving investors—are common across financial markets. Preliminary evidence from international equity markets is consistent with this conjecture and suggests that the asymmetry documented here may represent a broader empirical regularity. Exploring the international dimension of AIR is an important direction for future research that we are currently pursuing.

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Tables

Table 1: Residual returns reverse while systematic returns continue. Each month, stocks are sorted into quintile portfolios using NYSE breakpoints on either the trailing one-month residual component RES (left panel) or the trailing one-month systematic component SYS (right panel). RES is the sum of formation-month residuals $\tilde{\epsilon}$ from the cross-sectional return decomposition in equation (3), following equation (10). SYS is the corresponding sum of formation-month systematic shocks $\tilde{r}$, following equation (11). Within earnings-announcement windows, we assign the residual to the systematic shock $\tilde{r}$ and set $\tilde{\epsilon}$ to zero, as in equations (5) and (6). Both components skip the final formation-month trading day. The first two rows report the month- m trailing one-month residual and systematic components for the portfolios. RET_m is the time-series average of value-cap-weighted pre-formation monthly returns; RET_{m+1} is the time-series average of post-formation monthly returns; and FF6 α_{m+1} is estimated from a time-series regression of those excess returns on the monthly FF6 factors. Newey–West t -statistics are reported in brackets below portfolio returns and FF6 alphas; boldface denotes statistical significance at the 95% confidence level. Characteristics are monthly portfolio medians averaged over time: IVOL is annualized idiosyncratic volatility; Size is market equity in USD billions; SUE is standardized unexpected earnings; Amihud is illiquidity scaled by 10^6 ; Share Turnover is CRSP monthly share volume divided by shares outstanding, in percent; N stocks is the average number of names; and Portfolio Turnover is one-way monthly turnover in portfolio weights. The sample period is January 1972–December 2022.

	RES-sorted portfolios					
	Low	2	3	4	High	High - Low
RES _{<i>m</i>} (%)	-8.67	-3.07	-0.09	2.91	8.73	17.40
SYS _{<i>m</i>} (%)	1.86	1.28	0.68	0.08	-0.49	-2.35
<i>Portfolio returns</i>						
RET _{<i>m</i>} (%)	-6.84 [-20.85]	-1.45 [-7.25]	1.07 [5.73]	3.66 [18.22]	10.73 [26.64]	17.57 [27.02]
RET _{<i>m+1</i>} (%)	1.54 [6.03]	1.29 [6.34]	1.06 [5.51]	0.80 [4.11]	0.43 [1.86]	-1.11 [-8.51]
FF6 α_{m+1} (%)	0.59 [5.64]	0.26 [6.49]	0.03 [0.76]	-0.22 [-5.25]	-0.48 [-9.42]	-1.08 [-7.42]
<i>Portfolio characteristics</i>						
IVOL _{<i>m</i>} (%)	31.91	23.64	22.45	23.95	34.00	2.09
Size _{<i>m</i>} (USD bn)	0.78	1.45	1.69	1.52	0.91	0.13
SUE _{<i>m</i>}	0.02	0.03	0.04	0.04	0.02	0.01
Amihud _{<i>m</i>}	0.10	0.05	0.04	0.04	0.07	-0.03
Share Turnover _{<i>m</i>} (%)	10.05	8.07	7.82	8.19	10.53	0.48
N stocks	499	403	387	401	507	9
Portfolio Turnover (%)	80.3	78.5	75.7	77.7	79.2	-1.1

Table 1: Residual returns reverse while systematic returns continue (continued).

	Systematic return (SYS) sorted portfolios					
	Low	2	3	4	High	High - Low
RES_m (%)	1.49	0.63	-0.09	-0.80	-1.55	-3.04
SYS_m (%)	-6.51	-1.99	0.74	3.47	7.94	14.45
<i>Portfolio returns</i>						
RET_m (%)	-5.80	-1.06	1.34	3.83	9.54	15.34
	[-16.21]	[-4.91]	[6.52]	[17.60]	[25.10]	[24.04]
RET_{m+1} (%)	0.48	0.94	1.14	1.22	1.34	0.86
	[1.90]	[4.32]	[5.70]	[6.06]	[6.03]	[5.35]
FF6 α_{m+1} (%)	-0.48	-0.11	0.10	0.18	0.35	0.84
	[-4.22]	[-1.62]	[2.27]	[3.08]	[3.89]	[4.39]
<i>Portfolio characteristics</i>						
$IVOL_m$ (%)	30.53	25.12	24.54	25.32	30.57	0.04
$Size_m$ (USD bn)	1.10	1.27	1.30	1.29	1.21	0.11
SUE_m	-0.01	0.02	0.03	0.04	0.06	0.07
$Amihud_m$	0.08	0.06	0.06	0.06	0.07	-0.01
Share Turnover $_m$ (%)	10.16	8.22	8.02	8.31	10.28	0.12
N stocks	468	426	422	425	457	-11
Portfolio Turnover (%)	78.9	79.8	79.2	79.8	80.0	1.1

Table 2: Asymmetric reversal and idiosyncratic volatility (WLS with Controls). The table reports Fama–MacBeth WLS regressions of next-month excess returns on idiosyncratic volatility and the positive and negative one-month residual return components. For WLS, we use market equity winsorized at the 80th NYSE percentile as the regression weight. Each column is a separate monthly cross-sectional regression. We report time-series average coefficients and t -statistics following the Newey–West procedure with automatic lag selection in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor. IVOL is the standard deviation of idiosyncratic returns ε over the formation month. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. All three measures skip the final formation-month trading day. In addition, RES^+ and RES^- also skip earnings announcements. We estimate idiosyncratic returns from the cross-sectional return decomposition in equation (3). The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. The sample period is January 1972–December 2022.

	Dependent variable: month $m + 1$ excess return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IVOL	−0.195 [−5.28]				0.336 [5.52]	−0.513 [−9.59]	0.050 [1.26]
RES^+		−0.055 [−11.39]		−0.063 [−12.36]	−0.085 [−10.39]		−0.068 [−11.31]
RES^-			−0.018 [−2.40]	−0.035 [−4.28]		−0.062 [−6.03]	−0.031 [−3.58]
Const.	0.014 [4.27]	0.019 [6.11]	0.004 [1.36]	0.014 [4.07]	0.016 [4.94]	0.010 [3.14]	0.014 [4.08]
R^2 (%)	9.1	9.2	9.2	9.7	9.4	9.5	9.7
Estimator	WLS	WLS	WLS	WLS	WLS	WLS	WLS
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Mispricing portfolios, idiosyncratic volatility, and AIR. Each month, stocks are sorted into quintiles using breakpoints from the screened formation sample on the stock-level mispricing score of [Stambaugh et al. \(2015\)](#). We denote this score by MIS_P; it ranges from zero, for the most underpriced stocks, to 100, for the most overpriced stocks. Underpriced is the lowest-score quintile and Overpriced is the highest-score quintile. Panel A reports monthly cross-sectional medians averaged over time, except Avg N, which is the average number of stocks in the portfolio. IVOL is annualized percent; AIR components RES⁺ and RES[−] are the sums of positive and negative residuals over the formation month, respectively, reported in monthly percent; and ME is market equity in USD billions. All three measures skip the final formation-month trading day. In addition, RES⁺ and RES[−] also skip earnings announcements. Panels B–D report monthly Fama–MacBeth WLS regressions of next-month excess returns within each quintile. Panel B includes IVOL and controls; Panel C includes AIR and controls; Panel D includes all three focal regressors and controls. The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. All regressions in Panels B–D weight stocks by their market equity, winsorized at the 80th NYSE percentile. Coefficients are time-series averages of monthly excess-return slopes, and R^2 is reported in percent. Newey–West t -statistics are reported in brackets; boldface denotes statistical significance at the 95% confidence level. The sample period is January 1972–December 2016 and requires nonmissing MIS_P, IVOL, RES⁺, and RES[−] at portfolio formation.

Variable	Mispricing portfolios				
	Underpriced	2	3	4	Overpriced
<i>Panel A: Portfolio characteristics</i>					
MIS _P	32.99	42.05	48.86	56.05	67.07
IVOL (%)	24.43	24.83	25.94	27.69	32.27
RES ⁺ (%)	10.82	11.04	11.54	12.31	14.18
RES [−] (%)	-11.09	-11.22	-11.62	-12.38	-14.30
ME (USD bn)	1.42	1.10	0.88	0.75	0.61
Avg N	385	384	384	384	384
<i>Panel B: IVOL</i>					
IVOL	-0.020	-0.152	-0.168	-0.205	-0.342
	[-0.39]	[-3.15]	[-3.34]	[-3.71]	[-6.11]
R ² (%)	8.96	9.53	10.57	11.30	11.49
Avg N	360	358	353	345	327
Controls	Yes	Yes	Yes	Yes	Yes

Table 3: Mispricing portfolios, idiosyncratic volatility, and AIR (continued).

Variable	Mispricing portfolios				
	Underpriced	2	3	4	Overpriced
<i>Panel C: AIR</i>					
RES ⁺	−0.055 [−8.93]	−0.070 [−11.38]	−0.069 [−10.18]	−0.069 [−11.09]	−0.076 [−10.51]
RES [−]	−0.063 [−7.50]	−0.054 [−7.43]	−0.051 [−5.95]	−0.036 [−3.71]	−0.017 [−1.56]
R ² (%)	9.62	10.17	11.31	12.08	12.34
Avg N	360	358	353	345	327
Controls	Yes	Yes	Yes	Yes	Yes
<i>Panel D: IVOL and AIR</i>					
IVOL	0.075 [0.90]	−0.060 [−0.73]	0.023 [0.25]	0.068 [0.85]	0.038 [0.40]
RES ⁺	−0.061 [−8.36]	−0.068 [−8.25]	−0.069 [−7.18]	−0.076 [−7.93]	−0.083 [−7.51]
RES [−]	−0.058 [−5.76]	−0.059 [−6.39]	−0.050 [−4.45]	−0.031 [−2.78]	−0.016 [−1.07]
R ² (%)	9.76	10.36	11.49	12.29	12.60
Avg N	360	358	353	345	327
Controls	Yes	Yes	Yes	Yes	Yes

Table 4: Residual-shock concentration and asymmetric reversal. The table reports Fama–MacBeth WLS regressions of next-month excess returns on the positive and negative one-month residual return components and their concentration measures. For WLS, we use market equity winsorized at the 80th NYSE percentile as the regression weight. Each column is a separate monthly cross-sectional regression. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. SYS is the sum of systematic shocks over the formation month. We obtain $CONC^+$ by summing squared positive residuals over the formation month, taking the square root, and dividing by RES^+ . Conversely, $CONC^-$ is the corresponding ratio for negative residuals and RES^- . The overall concentration measure $CONC$ is the sum of $CONC^+$ and $CONC^-$. Column (4) replaces the two signed concentration measures with $CONC$. Columns (3) and (4) also include the one-month systematic component SYS . All measures skip the final formation-month trading day. Within earnings-announcement windows, residuals are assigned to SYS and set to zero in all RES - and $CONC$ -based measures. We report time-series average coefficients and t -statistics following the Newey–West procedure with automatic lag selection in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor. We estimate residuals from the cross-sectional return decomposition in equation (3). The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. The sample period is January 1972–December 2022.

Dependent variable: month $m + 1$ excess return				
	(1)	(2)	(3)	(4)
RES^+	−0.063 [−12.36]	−0.053 [−11.84]	−0.053 [−11.61]	−0.054 [−11.77]
RES^-	−0.035 [−4.28]	−0.022 [−2.87]	−0.022 [−2.90]	−0.022 [−2.91]
$CONC^+$		0.010 [4.78]	0.007 [3.68]	
$CONC^-$		0.015 [5.53]	0.013 [5.40]	
SYS			0.033 [4.86]	0.033 [4.88]
$CONC$				0.010 [6.41]
Const.	0.014 [4.07]	0.016 [4.92]	0.016 [5.00]	0.013 [4.19]
R^2 (%)	9.7	9.8	10.5	10.5
Estimator	WLS	WLS	WLS	WLS
Controls	Yes	Yes	Yes	Yes

Table 5: Short-term characteristics. The table defines the short-term characteristics used in the spanning tests. Daily characteristics are formed from observations in month m ; the one-day-skipped version skips the final formation-month trading day before construction. Predicted signs refer to Fama–MacBeth regressions of next-month excess returns on the characteristic. The references identify the papers behind the characteristic definition or economic channel.

Characteristic	Description	Pred. Sign	References
<i>Low Volatility</i>			
IVOL ^{FF3}	Std. dev. of daily FF3 residuals in month m .	–	Ang et al. (2006)
Ret Vol	Std. dev. of daily excess returns in month m .	–	Ang et al. (2006)
<i>Lottery preferences</i>			
Skew	Skewness of daily raw returns in month m .	–	Barberis and Huang (2008) ; Mitton and Vorkink (2007) ; Bali et al. (2016)
ISkew ^{FF3}	Skewness of daily FF3 residuals in month m .	–	Mitton and Vorkink (2007) ; Boyer et al. (2010)
Coskew	CAPM residual coskewness with squared demeaned market excess returns in month m .	–	Harvey and Siddique (2000)
MAX	Maximum daily raw return in month m .	–	Bali et al. (2011)
MAX5	Average of the five largest daily raw returns in month m .	–	Bali et al. (2017)
SMAX	Average of the five largest daily raw returns divided by 252-day daily return volatility.	–	Asness et al. (2020)
<i>Liquidity</i>			
Lag Ret	Sum of daily excess returns in month m .	–	Jegadeesh (1990) ; Fu (2009) ; Huang et al. (2010) ; Hou and Loh (2016)
Amihud	Average daily $ r $ divided by dollar volume in month m .	+	Amihud (2002) ; Han and Lesmond (2011) ; Hou and Loh (2016)
Zero Trades	Actual-month turnover-adjusted number of zero-volume days in month m .	+	Lesmond et al. (1999) ; Liu (2006) ; Han and Lesmond (2011)
Spread	Corwin–Schultz high–low effective bid–ask spread estimate in month m .	+	Amihud and Mendelson (1986) ; Corwin and Schultz (2012) ; Hou and Loh (2016)
Turnover	Average daily share turnover in month m .	–	Lee and Swaminathan (2000) ; Datar et al. (1998) ; Chordia et al. (2001)

Table 6: Spanning regressions for short-term characteristics. Panel A reports monthly Fama–MacBeth WLS regressions of each one-day-skipped characteristic on RES^+ and RES^- , together with the predicted return sign and average adjusted R^2 in percent. The remaining panels report full-sample Fama–MacBeth WLS regressions of next-month excess returns on short-term characteristics. Panel B reports standalone characteristic slopes. Panel C adds RES^+ and RES^- using one-day-skipped characteristics. Panels D and E add the one-day-skipped concentration measure CONC and systematic component SYS, respectively. The overall concentration measure is the sum of $CONC^+$ and $CONC^-$. The residual, systematic, and concentration measures skip the final formation-month trading day. Within earnings-announcement windows, residuals are assigned to SYS and set to zero in all RES^- and CONC-based measures. The set of controls in the return-predictability regressions in Panels B–E includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. They use market equity winsorized at the 80th NYSE percentile as the regression weight. Characteristic definitions are in Table 5. Skew, FF3 skewness, and coskewness are divided by 100, and Amihud is multiplied by 10^6 ; all other characteristics enter in the units described in Table 5. Lag Ret is omitted from Panel E because it equals $RES^+ + RES^- + SYS$. Panel A coefficients are in characteristic units per unit of the residual component; Panels B–E coefficients are monthly excess-return slopes per unit of the characteristic. Newey–West t -statistics are reported in brackets; boldface denotes statistical significance at the 95% confidence level. The sample period is January 1972–December 2022.

Variable	IVOL ^{FF3}	Ret Vol	Skew	ISkew ^{FF3}	Coskew	MAX	MAX5	SMAX	Lag Ret	Amihud	Zero Trades	Spread	Turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
<i>Panel A: Predicted signs and residual fit</i>													
Pred. sign	–	–	–	–	–	–	–	–	–	+	+	+	–
RES^+	0.075 [58.91]	0.085 [65.47]	0.034 [22.92]	0.029 [23.27]	–0.000 [–3.17]	0.310 [48.06]	0.155 [152.47]	3.380 [19.74]	0.966 [130.52]	0.829 [3.94]	0.083 [1.73]	0.018 [30.80]	0.026 [7.19]
RES^-	–0.063 [–75.87]	–0.070 [–54.04]	0.024 [19.30]	0.022 [20.75]	0.001 [5.59]	–0.062 [–17.44]	–0.029 [–18.87]	1.708 [20.93]	0.942 [127.73]	–1.247 [–4.25]	–0.334 [–4.15]	–0.025 [–31.70]	–0.021 [–6.01]
Adj. R^2 (%)	67.6	64.1	7.0	5.3	1.0	50.0	65.1	24.5	59.2	3.6	0.3	34.7	16.4
<i>Panel B: Standalone regressions</i>													
Characteristic	–0.169 [–4.62]	–0.143 [–3.95]	0.017 [0.83]	0.028 [1.54]	0.005 [0.06]	–0.035 [–3.93]	–0.136 [–5.17]	–0.003 [–4.87]	–0.019 [–4.68]	–0.001 [–0.22]	–0.000 [–1.33]	–0.222 [–2.25]	–0.193 [–2.52]
<i>Panel C: Spanning regressions</i>													
Characteristic	–0.026 [–0.72]	0.015 [0.35]	0.136 [5.43]	0.140 [6.84]	–0.004 [–0.05]	0.051 [5.86]	0.144 [3.93]	0.002 [3.51]	0.035 [5.30]	0.003 [0.71]	–0.000 [–1.34]	–0.080 [–0.89]	0.083 [0.97]
RES^+	–0.062 [–12.09]	–0.064 [–10.84]	–0.067 [–12.26]	–0.067 [–12.52]	–0.063 [–12.27]	–0.078 [–12.01]	–0.085 [–10.17]	–0.075 [–10.32]	–0.097 [–11.84]	–0.062 [–12.57]	–0.063 [–12.40]	–0.062 [–12.59]	–0.062 [–12.04]
RES^-	–0.036 [–4.52]	–0.034 [–4.43]	–0.038 [–4.60]	–0.038 [–4.63]	–0.035 [–4.28]	–0.032 [–4.03]	–0.031 [–4.13]	–0.037 [–4.53]	–0.068 [–7.26]	–0.035 [–4.25]	–0.034 [–4.23]	–0.036 [–4.55]	–0.036 [–4.65]

Table 6: Spanning regressions for short-term characteristics (continued).

Variable	IVOL ^{FF3}	Ret Vol	Skew	ISkew ^{FF3}	Coskew	MAX	MAX5	SMAX	Lag Ret	Amihud	Zero Trades	Spread	Turnover
<i>Panel D: Spanning regressions with CONC</i>													
Characteristic	−0.059	−0.013	0.078	0.075	−0.010	0.031	0.107	0.002	0.033	0.003	−0.000	−0.071	0.070
	[−1.65]	[−0.32]	[3.44]	[4.31]	[−0.13]	[3.52]	[2.94]	[2.88]	[4.88]	[0.73]	[−1.30]	[−0.79]	[0.83]
RES ⁺	−0.049	−0.053	−0.058	−0.057	−0.053	−0.065	−0.071	−0.065	−0.086	−0.053	−0.054	−0.053	−0.053
	[−10.58]	[−9.68]	[−12.15]	[−12.56]	[−11.86]	[−11.91]	[−9.90]	[−9.96]	[−11.48]	[−12.03]	[−12.19]	[−12.19]	[−11.53]
RES [−]	−0.026	−0.024	−0.027	−0.026	−0.022	−0.023	−0.022	−0.025	−0.055	−0.022	−0.022	−0.023	−0.023
	[−3.28]	[−3.18]	[−3.34]	[−3.33]	[−2.83]	[−3.00]	[−2.88]	[−3.21]	[−6.37]	[−2.80]	[−2.78]	[−2.98]	[−3.15]
CONC	0.012	0.012	0.009	0.010	0.012	0.010	0.010	0.011	0.010	0.012	0.012	0.012	0.012
	[6.61]	[6.77]	[5.68]	[5.94]	[6.83]	[5.89]	[6.45]	[6.22]	[6.41]	[6.72]	[6.68]	[6.39]	[6.93]
<i>Panel E: Spanning regressions with CONC and SYS</i>													
Characteristic	−0.064	−0.018	0.034	0.033	0.012	0.009	−0.000	0.000		0.005	−0.000	−0.043	0.049
	[−1.82]	[−0.45]	[1.43]	[1.73]	[0.16]	[0.96]	[−0.01]	[0.27]		[1.03]	[−1.37]	[−0.50]	[0.65]
RES ⁺	−0.049	−0.052	−0.055	−0.055	−0.053	−0.057	−0.053	−0.056		−0.053	−0.053	−0.053	−0.053
	[−10.31]	[−9.71]	[−10.62]	[−11.17]	[−11.68]	[−9.52]	[−7.20]	[−8.28]		[−11.91]	[−12.04]	[−12.36]	[−11.28]
RES [−]	−0.026	−0.024	−0.024	−0.024	−0.022	−0.023	−0.023	−0.022		−0.022	−0.022	−0.023	−0.023
	[−3.32]	[−3.21]	[−2.93]	[−2.97]	[−2.87]	[−2.93]	[−3.05]	[−2.80]		[−2.84]	[−2.82]	[−2.93]	[−3.10]
CONC	0.010	0.010	0.009	0.009	0.010	0.010	0.010	0.010		0.010	0.010	0.010	0.010
	[6.49]	[6.63]	[5.87]	[5.96]	[6.51]	[6.08]	[6.58]	[6.14]		[6.44]	[6.40]	[6.19]	[6.63]
SYS	0.033	0.032	0.032	0.032	0.033	0.032	0.032	0.032		0.033	0.033	0.033	0.033
	[4.91]	[4.81]	[4.60]	[4.55]	[4.96]	[4.44]	[4.20]	[4.54]		[4.89]	[4.88]	[4.98]	[4.94]

Table 7: Residual reversal factor performance. The table reports the performance of competing reversal factors. Each month, we sort stocks into value-cap-weighted quintile portfolios using NYSE breakpoints on STREV, RES, or ASRES. STREV and the three RES factors are long the lowest quintile and short the highest quintile of their respective formation-month return measures. ASRES is long the highest quintile and short the lowest quintile of the out-of-sample m-spline forecast of residual return in equation (28). From left to right, the columns move from raw formation-month returns to residual returns from increasingly rich decompositions and, finally, to the asymmetric residual return forecast. STREV is the stock’s raw return over the formation month. In the three RES columns, we obtain daily residual returns from the cross-sectional return decomposition in equation (3), using, respectively, firm characteristics; firm characteristics and industries; and firm characteristics and industries with the earnings-announcement adjustment. RES is the sum of these residual returns over the formation month, following equation (10). When forming the STREV, RES, and ASRES sorting variables, we skip the final formation-month trading day. Within earnings-announcement windows, in the final RES specification and ASRES, we assign the residual to the systematic shock $\tilde{r}$ and set $\tilde{\epsilon}$ to zero, as in equations (5) and (6). The table reports excess returns, factor-model alphas, annualized volatility, and annualized Sharpe ratios. Starting with the CAPM market factor, FF3 adds size and value factors, FF6 further adds profitability, investment, and momentum factors, and FF6+REV additionally includes the short-term reversal factor. Newey–West t -statistics are in brackets; boldface denotes statistical significance at the 95% confidence level. The sample period is January 1974–December 2022.

	Reversal Factor				
	STREV	RES			ASRES
Excess Return	0.26 [1.80]	0.88 [7.54]	0.95 [7.54]	1.07 [8.25]	1.18 [10.56]
CAPM alpha	0.08 [0.46]	0.80 [6.17]	0.87 [7.20]	1.01 [7.83]	1.21 [15.02]
FF3 alpha	0.03 [0.18]	0.73 [9.08]	0.81 [11.48]	0.96 [12.66]	1.17 [11.83]
FF6 alpha	0.27 [1.45]	0.85 [5.49]	0.91 [6.89]	1.03 [7.17]	1.08 [8.04]
FF6 + REV alpha		0.69 [8.37]	0.78 [8.71]	0.90 [9.62]	0.98 [13.69]
Volatility (%)	14.1	6.9	6.2	6.1	5.6
SR	0.22	1.52	1.82	2.12	2.55
Characteristics		✓	✓	✓	✓
Industries			✓	✓	✓
Zero EAD				✓	✓
Forecast model					✓

Table 8: Factor loadings of ASRES. The table reports factor loadings from a regression of the asymmetric residual reversal factor, ASRES, on MKT (market), SMB (size), HML (value), RMW (profitability), CMA (investment), UMD (momentum), and REV (raw return short-term reversal). Each month, we sort stocks into value-cap-weighted quintile portfolios using NYSE breakpoints on ASRES. ASRES is the negative of the out-of-sample m-spline forecast of the residual return in equation (28); equivalently, its factor is long stocks with the highest forecasted residual return and short stocks with the lowest forecasted residual return. When forming ASRES, we skip the final formation-month trading day. Within earnings-announcement windows, we assign the residual to the systematic shock $\tilde{r}$ and set $\tilde{\varepsilon}$ to zero, as in equations (5) and (6). Newey–West t -statistics are in brackets; boldface denotes statistical significance at the 95% confidence level. The sample period is January 1974–December 2022.

	MKT	SMB	HML	RMW	CMA	UMD	REV
ASRES	−0.02 [−1.59]	−0.11 [−4.11]	0.11 [3.28]	0.17 [4.51]	0.05 [1.16]	0.08 [2.86]	0.23 [8.21]

Table 9: ASRES robustness by size and sample period. Each month, stocks are sorted into value-cap-weighted quintiles using NYSE breakpoints on the out-of-sample m-spline forecast of residual return. ASRES is long the highest-forecast quintile and short the lowest-forecast quintile. The size-group columns form ASRES separately within monthly NYSE market-equity groups. The investable-size screen removes the Nano bucket, which is at or below the 1st percentile. Reported buckets therefore begin with Micro, above the 1st and at or below the 20th percentile; Small is above the 20th and at or below the 50th percentile; Large is above the 50th and at or below the 80th percentile; and Mega is above the 80th percentile. The sample-period columns form ASRES separately before and after decimalization. April 2001 is the first post-decimalization month; observations through March 2001 are pre-decimalization. Returns and alphas are in percent per month; volatility is annualized percent; Sharpe ratios are annualized. Starting with the CAPM market factor, the FF3 model adds size and value factors; FF5 further adds profitability and investment factors; FF6 also includes momentum; and REV is the short-term reversal factor. Newey–West t -statistics are reported in brackets; boldface denotes statistical significance at the 95% confidence level. The sample period is January 1974–December 2022.

	Size group				Sample period	
	Micro	Small	Large	Mega	Pre-dec.	Post-dec.
Excess Return	1.35 [7.16]	1.43 [10.71]	1.16 [9.23]	0.89 [8.28]	1.65 [15.85]	0.60 [6.38]
CAPM alpha	1.33 [6.69]	1.44 [17.30]	1.16 [10.09]	0.92 [10.28]	1.66 [18.37]	0.64 [6.98]
FF3 alpha	1.36 [5.90]	1.40 [13.60]	1.11 [9.86]	0.87 [8.33]	1.57 [15.32]	0.65 [7.38]
FF5 alpha	1.46 [6.68]	1.37 [12.23]	1.03 [10.60]	0.81 [8.29]	1.49 [13.14]	0.55 [6.88]
FF6 alpha	1.40 [6.29]	1.35 [7.82]	1.02 [6.17]	0.81 [9.77]	1.52 [11.30]	0.54 [6.82]
FF6 + REV alpha	1.25 [6.07]	1.23 [12.30]	0.92 [7.65]	0.73 [7.95]	1.39 [12.91]	0.51 [6.42]
Volatility (%)	13.7	7.0	6.9	6.1	5.4	5.1
SR	1.18	2.43	2.03	1.74	3.66	1.41

Figures

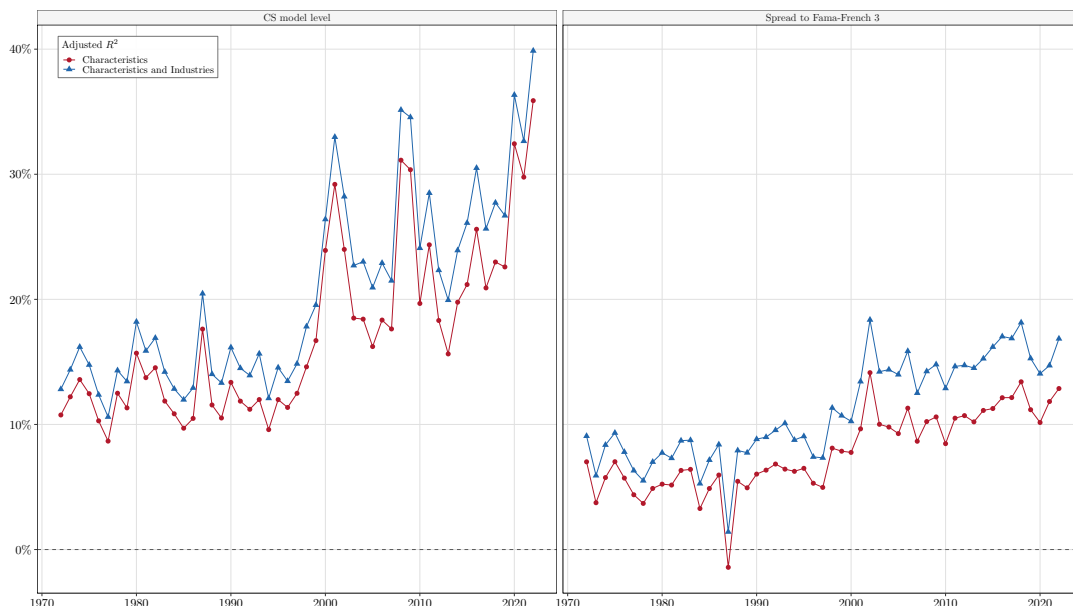


Figure 1: Goodness of fit relative to the Fama-French benchmark. This figure compares annual adjusted R^2 for the daily cross-sectional return decompositions in equation (3) with the stock-level Fama-French three-factor benchmark. The red line with circle markers is the restricted characteristics-only specification, and the blue line with triangle markers is the baseline characteristics-and-industries specification. The left panel shows annual adjusted R^2 , in percent. The right panel shows the percentage-point spread between each cross-sectional specification and the Fama-French benchmark, evaluated on the annual daily cross-sectional total-variation scale; positive values indicate higher fit than the benchmark. We compute annual adjusted R^2 by aggregating residual and total sums of squares within year and then applying the degrees-of-freedom adjustment. For the WLS cross-sectional models, sums of squares use the market-equity estimation weights. Sample period: January 1972–December 2022.

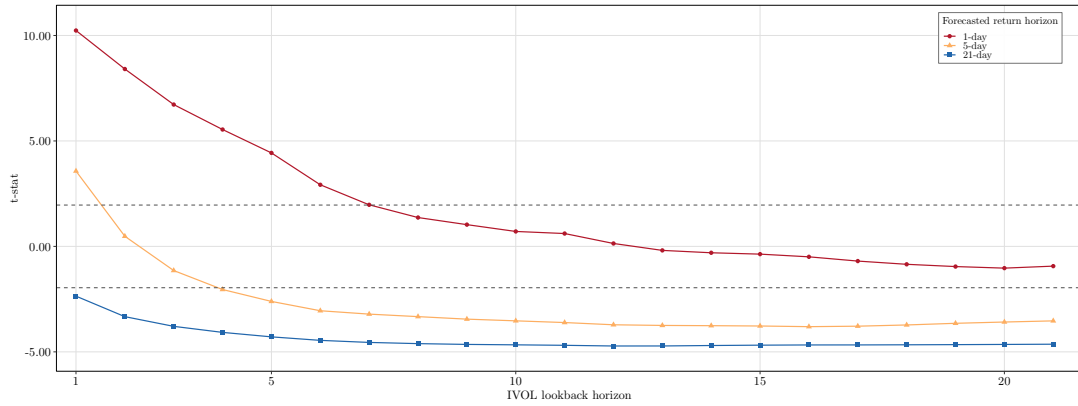


Figure 2: Horizon dependence of the IVOL effect. This figure plots Newey–West t -statistics from predictive Fama–MacBeth regressions of returns on IVOL. We measure returns over the following one-day (red line with circle markers), one-week (orange line with triangle markers), and one-month (blue line with square markers) horizons. The horizontal axis varies the lookback horizon over which IVOL is computed, from 1 to 21 days prior to the start of the return measurement window. The vertical axis is the Newey–West t -statistic on the IVOL coefficient. The regressions include the controls in Table 2 and use market-equity WLS weights. The dashed horizontal lines mark the two-sided 5% significance thresholds. Sample period: January 1972–December 2022.

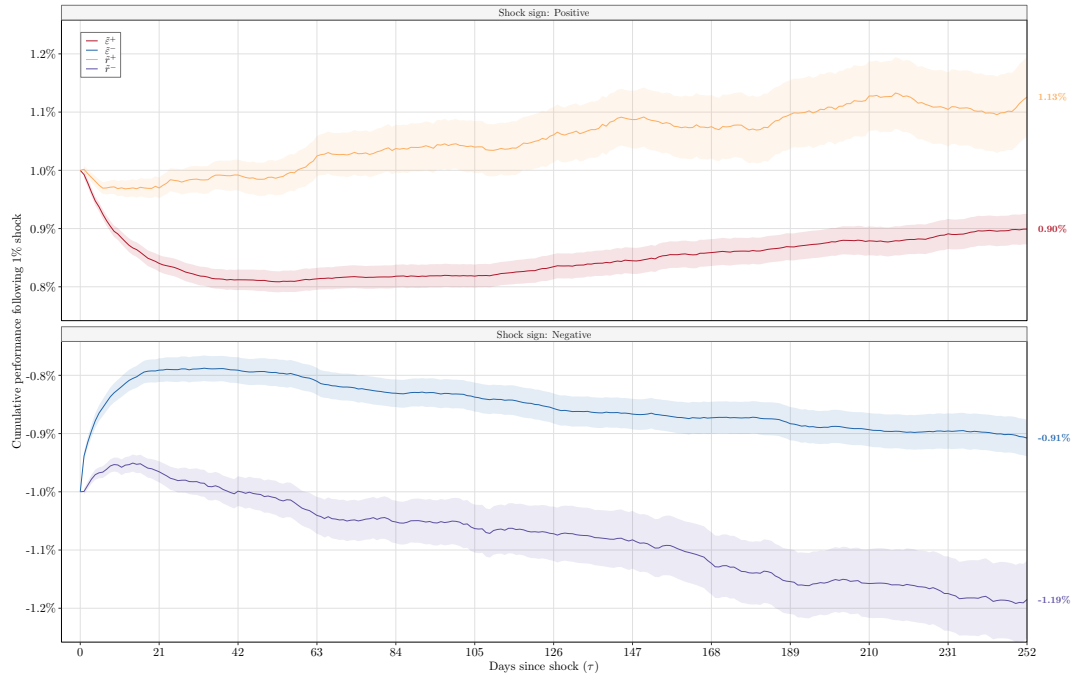


Figure 3: Impulse-response functions from the dense Fama–MacBeth regression. This figure plots expected compounded cumulative returns from the dense daily Fama–MacBeth regression in equation (19), following the impulse-response construction in equations (20)–(21). The vertical axis is cumulative performance in percent following a 1% shock. The four entries are $\tilde{\varepsilon}^+$ (solid red line), $\tilde{\varepsilon}^-$ (solid blue line), $\tilde{r}^+$ (solid orange line), and $\tilde{r}^-$ (solid purple line). Shaded regions are 95% Newey–West confidence bands. The top panel reports positive-shock responses and the bottom panel negative-shock responses. Positive components start at +1%, and negative components start at −1%. Reversal corresponds to movement toward the initial shock value; momentum corresponds to movement away from it. Bold labels at the right report cumulative performance on day 252. Sample period: January 1972–December 2022.

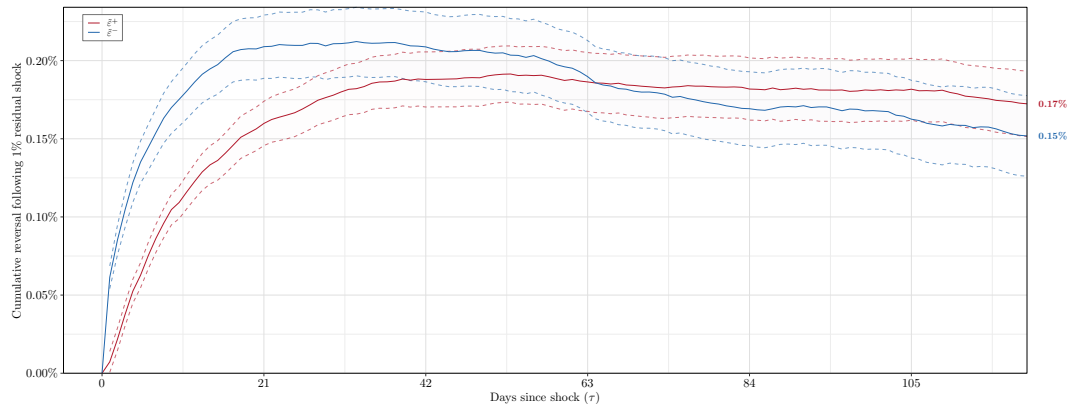


Figure 4: Zooming in on residual impulse-response functions. This figure is a zoomed version of Figure 3. It plots expected compounded cumulative return responses from the dense daily Fama–MacBeth regression in equation (19), following positive (red) and negative (blue) 1% residual shocks, over the first 120 trading days. The vertical axis is cumulative reversal in percent, measured as the distance between each response and its signed initial-shock value; both paths therefore start at zero. Ribbons show 95% Newey–West confidence bands. The sample period is January 1972–December 2022.

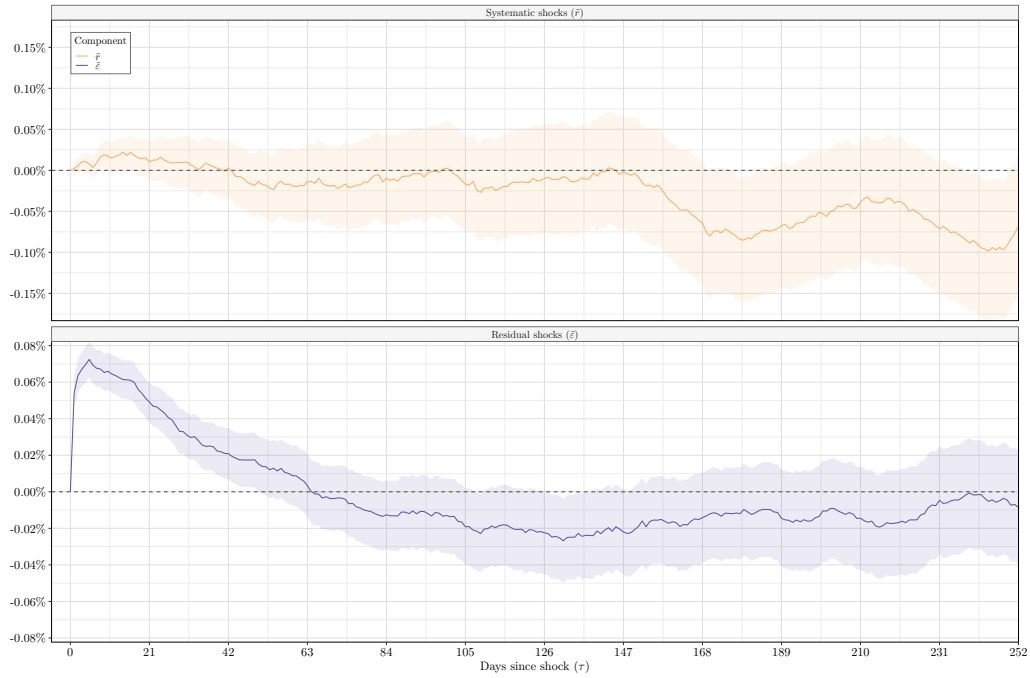


Figure 5: Asymmetry in impulse-response functions. This figure plots sums of signed impulse-response functions constructed from equations (20)–(21). The vertical axis is the sum of the positive- and negative-shock impulse responses, in percentage points. The top panel shows the sum for systematic components, and the bottom panel shows $IR^{\varepsilon^+}(\tau) + IR^{\varepsilon^-}(\tau)$ for residual components. The dashed horizontal line marks zero; under perfect sign symmetry, the plotted sum equals zero. Positive values indicate that the positive component reverts more slowly than the negative. Shaded regions are 95% Newey–West confidence bands. Sample period: January 1972–December 2022.

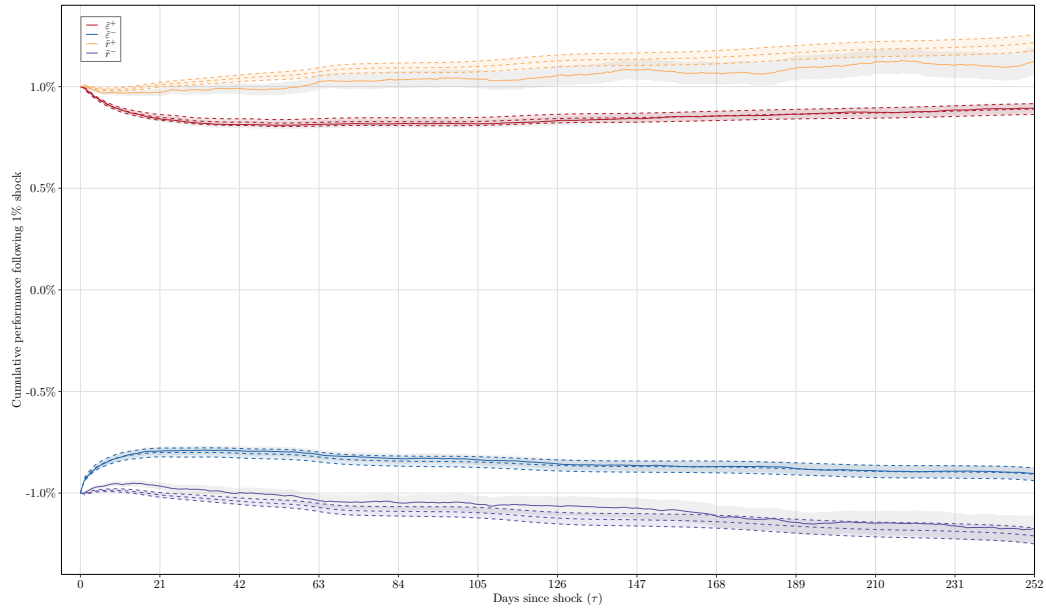


Figure 6: Impulse-response comparison: dense and spline Fama–MacBeth regressions. This figure compares expected compounded cumulative returns from the dense daily Fama–MacBeth regression in equation (19) with those from the spline regression in equation (22), using the impulse-response construction in equations (20)–(21). The vertical axis is cumulative performance in percent following a 1% shock. Solid lines are dense-regression responses with 1,008 slope parameters. Dashed lines are spline-regression responses with 81 slope parameters; shaded regions are 95% Newey–West confidence bands. Colors identify the same four return components and sign convention as in Figure 3. Sample period: January 1972–December 2022.

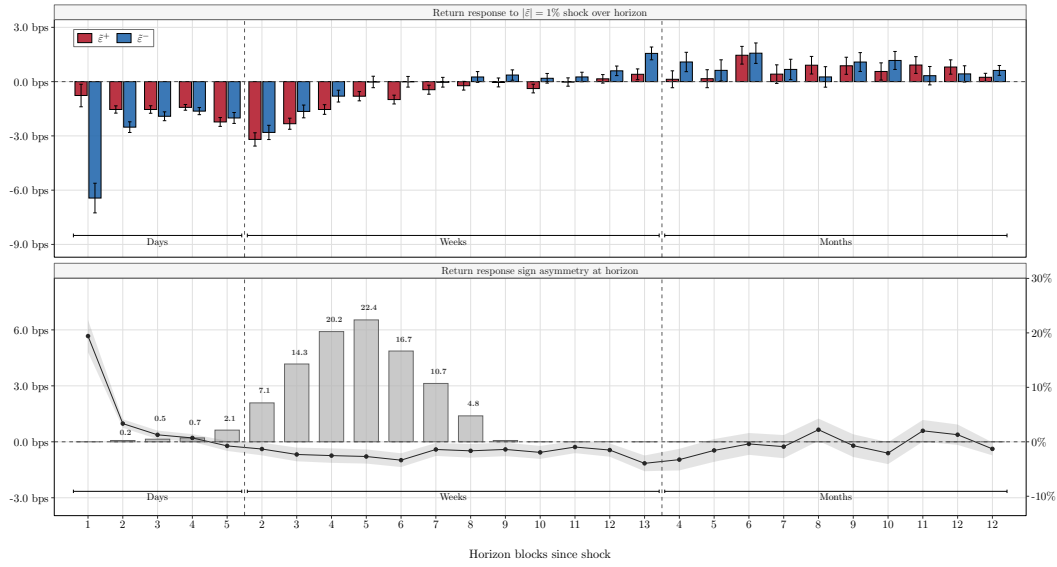


Figure 7: Residual reversal timing and monthly aggregation weights. This figure links spline-implied residual return responses from equation (22) to the monthly aggregation weights derived in equation (C.9). The horizontal axis in both panels is the horizon block since the residual shock; vertical dashed lines separate daily, weekly, and monthly blocks. The top panel shows residual return responses, in basis points, by horizon block for a 1% absolute shock to $\tilde{\varepsilon}^+$ (red bars) and $\tilde{\varepsilon}^-$ (blue bars). Black error bars are 95% Newey–West confidence intervals. A daily block is the expected return response over that trading-day horizon; a weekly block is the cumulative expected return response over the trading days in that weekly horizon block. Negative values indicate a return response opposite to the signed initial shock, and therefore reversal, for both signs. The bottom panel overlays the residual-response sign asymmetry (solid dark line with points, left axis in basis points) and the normalized monthly aggregation weights (gray bars, right axis in percent). Positive asymmetry values indicate stronger reversal after negative residual shocks, and negative values indicate stronger reversal after positive residual shocks. The weights load most heavily around the middle of the 1-to-40 lag window, after the first-week negative-shock reversal differential has largely dissipated. Sample period: January 1972–December 2022.

A Additional Figures

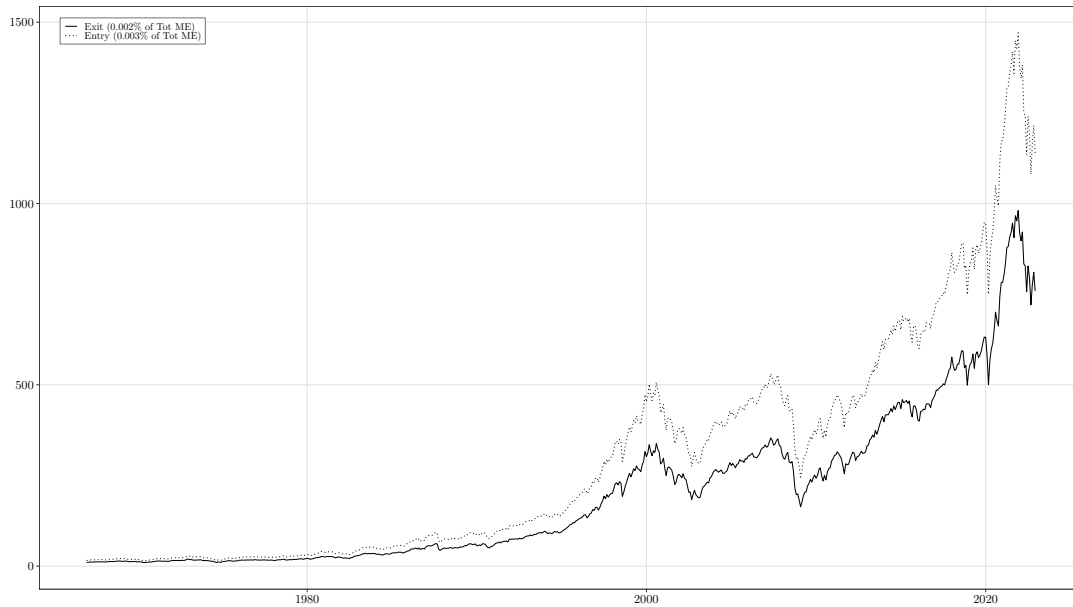


Figure A.1: Market equity cutoffs. This figure plots the monthly market-equity cutoffs implied by the investable-sample entry and exit rules. The vertical axis is market equity in USD millions. The dotted black line is the entry cutoff, equal to 0.003% of total U.S. equity market capitalization, and the solid black line is the exit cutoff, equal to 0.002%. Stocks enter the investable sample when their market equity exceeds the entry cutoff and are dropped when it falls below the exit cutoff. Hysteresis between the two cutoffs limits turnover from stocks moving in and out of the sample. Sample period: January 1972–December 2022.

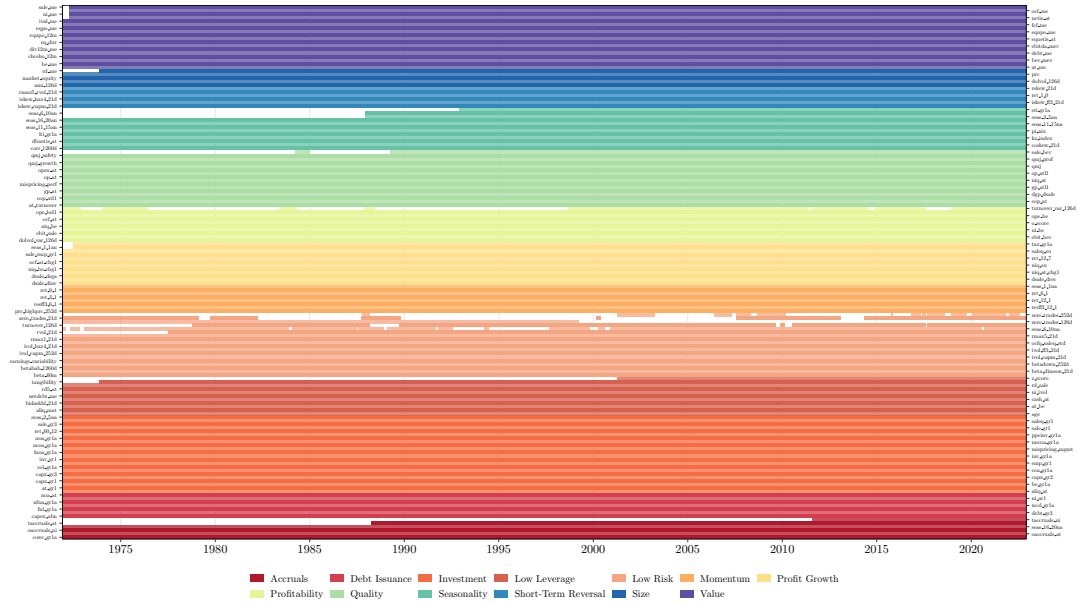


Figure A.2: Characteristics included in the cross-sectional regression. This figure reports which firm characteristics from [Jensen et al. \(2023\)](#) (JKP) enter the cross-sectional return decomposition in equation (3). The horizontal axis is calendar month, and the left and right vertical axes list firm characteristics. A colored cell indicates that the characteristic is included in month t ; a blank cell indicates that it is not included. Colors group characteristics by JKP thematic category. A characteristic enters when at least 40% of sample stocks have a valid observation and is removed when coverage falls below 20%. Among characteristics that pass this coverage screen, near-collinear characteristics are represented by one date- t duplicate-group member. Sample period: January 1972–December 2022.

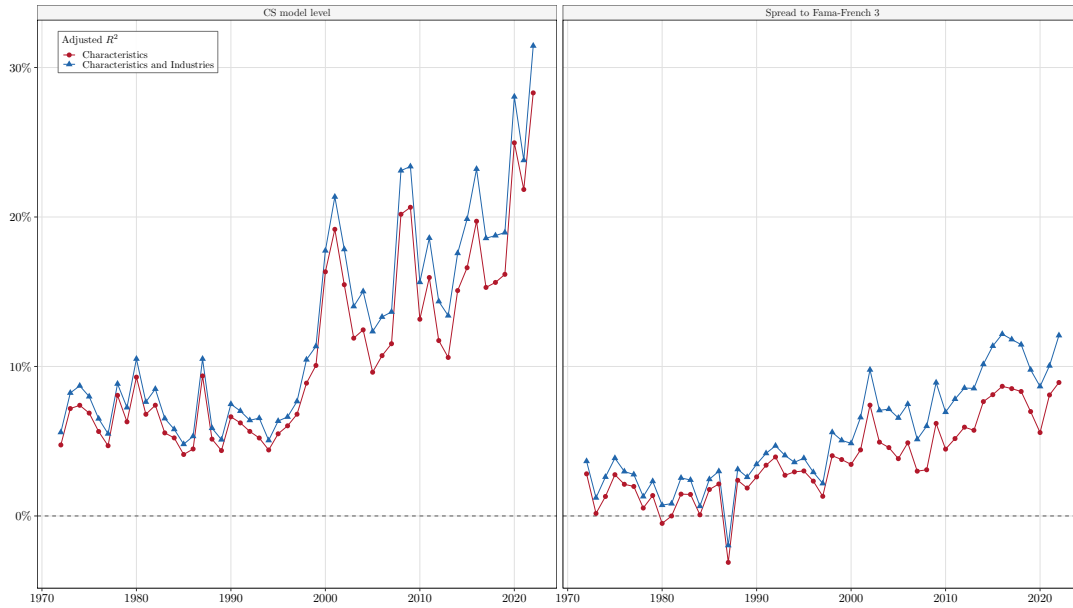


Figure A.3: Equal-weighted cross-sectional return fit. This figure repeats Figure 1 using equal-weighted OLS cross-sectional regressions. The left panel plots annual adjusted R^2 values for the characteristics-only and characteristics-and-industries specifications. The right panel plots each specification's annual adjusted- R^2 spread relative to the Fama–French three-factor benchmark, also evaluated using equal weights. Circle markers denote the characteristics-only specification and triangle markers denote the characteristics-and-industries specification. Sample period: January 1972–December 2022.

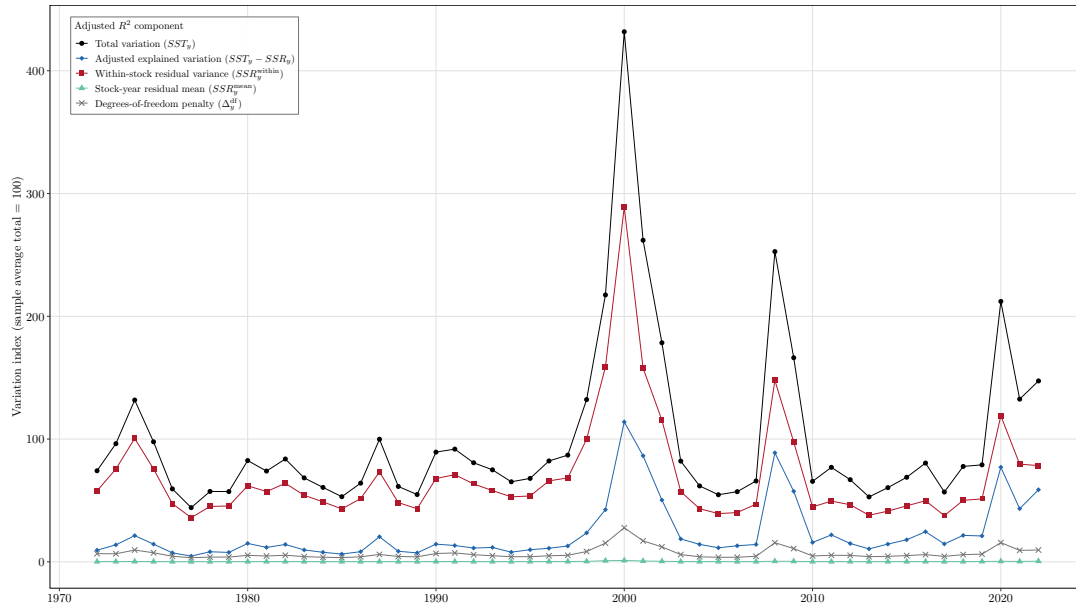


Figure A.4: Variance decomposition of the cross-sectional return fit. This figure decomposes the annual variation behind the adjusted R^2 for the value-cap-weighted characteristics-and-industries specification in equation (3). The vertical axis is a variation index that scales each series by the sample-average $\widetilde{TSS}_y$, so the total-variation series averages 100. The black line with circle markers is total variation ($\widetilde{TSS}_y$). The remaining entries decompose total variation into adjusted explained variation ($\widetilde{TSS}_y - \widetilde{RSS}_y$, blue diamonds), within-stock residual variance ($\widetilde{RSS}_y^{\text{within}}$, red squares), and the stock-year residual-mean component ($\widetilde{RSS}_y^{\text{mean}}$, green triangles). Gray x-marks show the degrees-of-freedom penalty (Δ_y^{df}). WLS weights are normalized within each daily cross-section before forming annual sums of squares. Sample period: January 1972–December 2022.

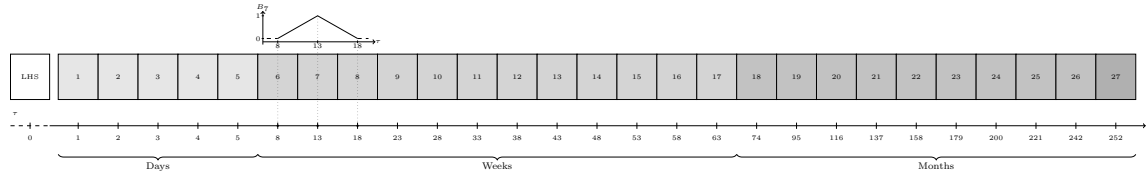


Figure A.5: Spline basis knot schedule. This figure summarizes the 27-term spline basis used in the spline Fama–MacBeth regression in equation (22). The numbered gray blocks are the basis functions, and the bottom axis gives the corresponding lag knots in trading days, grouped into days, weeks, and months. Basis knots are placed at lags 1–5 (daily resolution), at weekly midpoints from lag 8 to lag 63, at monthly midpoints from lag 74 to lag 242, and at the one-year horizon (lag 252). The left white block marks the dependent-variable date; its dashed timeline segment indicates that it is not part of the right-hand-side lag grid. The inset shows a representative degree-1 piecewise-linear tent basis function.

B Decomposing RSS_y variation

Broadly speaking, the unexplained residual sum of squares RSS_y could be high, in any given year, because firms have large average (positive or negative) residuals (recall that only the cross-sectional average residual is zero by construction every day, but any given firm could have a systematic bias in its residual on average within a year) and/or because they have large time-series standard deviation of residuals.

The time series in Figure 1 reflects movements in both the residual and total weighted sums of squares. Figure A.4 separates these forces for the baseline characteristics-and-industries specification. Adjusted explained variation equals $\widetilde{TSS}_y - \widetilde{RSS}_y$. To decompose the residual side, define the within-stock and stock-year mean components as

$$\widetilde{RSS}_y^{\text{within}} = \sum_i \sum_{t \in y} \omega_{it} (\varepsilon_{it} - \bar{\varepsilon}_{iy}^\omega)^2, \quad (\text{B.1})$$

$$\widetilde{RSS}_y^{\text{mean}} = \sum_i \left(\sum_{t \in y} \omega_{it} \right) (\bar{\varepsilon}_{iy}^\omega)^2, \quad (\text{B.2})$$

where $\bar{\varepsilon}_{iy}^\omega$ is the weighted average residual for stock i in year y . These components partition $\widetilde{TSS}_y$ exactly:

$$\widetilde{TSS}_y = (\widetilde{TSS}_y - \widetilde{RSS}_y) + \widetilde{RSS}_y^{\text{within}} + \widetilde{RSS}_y^{\text{mean}}. \quad (\text{B.3})$$

We scale the plotted series by the sample-average $\widetilde{TSS}_y$, so the total-variation series averages 100 over the sample. Thus the R^2 rises when explained variation approaches total variation. The decomposition shows that the large movements in total variation, especially around the internet boom, primarily reflect movements in within-stock residual variance rather than stock-year residual means. This pattern explains why the R^2 in Figure 1 does not simply track total volatility. Around the 2000 dot-com bubble, total variation surges. Both adjusted explained variation and within-stock residual variance rise sharply, with total variation rising more than adjusted residual variation. The R^2 therefore improves in 2000 even though residual variance also spikes. In later years, residual variance falls relative to total variation, and the R^2 reaches its highest values. The residual-variance spike around 2000 links the decomposition to the idiosyncratic-volatility literature: it resembles the increase in firm-level idiosyncratic risk documented by [Campbell et al. \(2001\)](#) and [Xu and Malkiel \(2003\)](#), while the subsequent decline is consistent with the later evidence reviewed in [Campbell et al.](#)

(2023). In our setting, we measure residuals after hedging a broad cross-sectional span of characteristics and industries, so the figure shows that economically meaningful idiosyncratic variation remains strongly time-varying after this richer adjustment.

C Monthly aggregation weights

This appendix derives the horizon weights that connect the daily residual response coefficients in the spline regression (22) to the monthly signed-residual regression. For simplicity, we abstract from return compounding within a month and assume 20 formation days, one skipped trading day, and 21 holding days. We focus on the positive residual measure RES^+ . The derivation for the negative residual case is analogous.

In the main text, $\text{RES}_{i,m}^+$ and $\text{RES}_{i,m}^-$ are the sums of positive and negative residuals over the stock-month-specific set $\mathcal{D}_{i,m}$, as defined in equations (12)–(13). We focus on the coefficient on $\text{RES}_{i,m}^+$ in the simple two-signal monthly projection

$$r_{i,m+1} = \alpha_m + \gamma_m^+ \text{RES}_{i,m}^+ + \gamma_m^- \text{RES}_{i,m}^- + \eta_{i,m+1}. \quad (\text{C.1})$$

Let γ^+ denote the time-series average of the monthly slopes γ_m^+ . For the representative derivation, index the 20 formation residuals by $d \in \{1, \dots, 20\}$. The skipped trading day is day 21, and the 21 holding-period returns are indexed by $t \in \{22, \dots, 42\}$. The additive return approximation writes the next-month return as

$$r_{i,m+1} \approx \sum_{t=22}^{42} r_{i,t}. \quad (\text{C.2})$$

Equation (22) estimates the daily response of returns to lagged residuals, conditional on the other lagged components in the daily specification. Let λ_τ^+ denote the time-series average spline-implied daily loading on positive residuals at event-time distance τ , using the paper’s lag convention. The direct part of a holding-period daily return that comes from formation-month positive residuals is

$$r_{i,t}^{+, \text{form}} = \sum_{d=1}^{20} \lambda_{t-d}^+ \tilde{\epsilon}_{i,d}^+. \quad (\text{C.3})$$

Plugging (C.3) into (C.2) gives the direct formation-month positive-residual contribution to the monthly return:

$$r_{i,m+1}^{+,form} \approx \sum_{t=22}^{42} \sum_{d=1}^{20} \lambda_{t-d}^+ \tilde{\epsilon}_{i,d}^+. \quad (C.4)$$

The monthly coefficient can be decomposed into this direct same-component channel and an aggregate remainder,

$$\gamma^+ = \gamma^{+,direct} + \delta^{+,other}. \quad (C.5)$$

The direct term captures the contribution of formation-month positive residuals in equation (C.4). The residual term $\delta^{+,other}$ collects the remaining covariance terms in the monthly projection, including the contribution of other lagged components and residual variation not captured by the direct positive-residual channel. We do not require these terms to be zero individually. The approximation is instead that their aggregate contribution is modest.

Because $RES_{i,m}^+$ sums the same positive residuals over the formation month, the direct component of the monthly slope aggregates the daily spline coefficients over all formation-day and holding-day pairs. Under the representative equal-weight formation window,

$$\gamma^{+,direct} \approx \frac{1}{20} \sum_{t=22}^{42} \sum_{d=1}^{20} \lambda_{t-d}^+. \quad (C.6)$$

Define

$$n_\tau = \#\{(d, t) : d \in \{1, \dots, 20\}, t \in \{22, \dots, 42\}, t - d = \tau\} \quad (C.7)$$

Then

$$\gamma^{+,direct} \approx \frac{1}{20} \sum_{\tau=2}^{41} n_\tau \lambda_\tau^+. \quad (C.8)$$

With the one-day skip, the nonzero event-time distances run from $\tau = 2$ to $\tau = 41$. The counts are

$$n_\tau = \begin{cases} \tau - 1, & 2 \leq \tau \leq 21, \\ 42 - \tau, & 22 \leq \tau \leq 41, \\ 0, & \text{otherwise.} \end{cases} \quad (C.9)$$

Thus the pair counts rise from 1 to 20, plateau at 20 for two adjacent event-time distances, and then fall back to 1. The corresponding coefficient weights are $n_\tau/20$. The

simpler 21-day, no-skip example in the main text has the same triangular logic: it shifts the first nonzero distance to lag 1 and peaks when the formation and holding months overlap most densely in event time.

In the data, this direct timing channel explains most of the monthly coefficient on RES^+ . In the two-signal monthly regression (C.1), the average coefficient is about $\gamma^+ = -1.28$. The direct triangular aggregation in (C.8) gives $\gamma^{+, \text{direct}} = -1.35$, leaving an aggregate remainder of $\delta^{+, \text{other}} = 0.07$. The triangular weights therefore capture the main timing force behind the connection between daily positive-residual responses and the one-month signed-residual slope, although they do not constitute an exact accounting identity for the monthly coefficient.

D Additional results

D.1 RES and IVOL

This subsection collects three robustness checks for the result in Table 2 that the asymmetric residual decomposition spans the idiosyncratic-volatility anomaly.

Table D.1 drops the six characteristic controls from the headline specification. The slope on RES^+ is -0.064 in the saturated regression, the asymmetry between the RES^+ and RES^- slopes is preserved, and the IVOL slope is statistically indistinguishable from zero once both signed residual components enter.

Table D.1: Asymmetric reversal and idiosyncratic volatility (WLS). The table reports Fama–MacBeth WLS regressions of next-month excess returns on idiosyncratic volatility and the positive and negative one-month residual return components. For WLS, we use market equity winsorized at the 80th NYSE percentile as the regression weight. Each column is a separate monthly cross-sectional regression. We report time-series average coefficients and t -statistics following the Newey–West procedure with automatic lag selection in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor. IVOL is the standard deviation of idiosyncratic returns ε over the formation month. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. All three measures skip the final formation-month trading day. In addition, RES^+ and RES^- also skip earnings announcements. We estimate idiosyncratic returns from the cross-sectional return decomposition in equation (3). The sample period is January 1972–December 2022.

	Dependent variable: month $m + 1$ excess return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IVOL	−0.197 [−2.72]				0.344 [4.47]	−0.542 [−7.26]	0.030 [0.72]
RES^+		−0.046 [−5.30]		−0.061 [−8.45]	−0.082 [−10.09]		−0.064 [−8.66]
RES^-			−0.006 [−0.50]	−0.036 [−3.63]		−0.062 [−5.46]	−0.034 [−3.19]
Const.	0.009 [5.32]	0.012 [6.70]	0.006 [3.20]	0.009 [5.26]	0.010 [5.86]	0.008 [4.50]	0.009 [5.30]
R^2 (%)	2.2	1.9	2.2	3.1	2.6	2.8	3.2
Estimator	WLS	WLS	WLS	WLS	WLS	WLS	WLS
Controls	No	No	No	No	No	No	No

Table D.2 replaces WLS with OLS, with the controls included. The slope on RES^+ is slightly larger in absolute value under OLS, the asymmetry between the two signed components is preserved, and the IVOL slope flips sign in column 5 and is insignificant in column 7.

Table D.2: Asymmetric reversal and idiosyncratic volatility (OLS with Controls). The table reports Fama–MacBeth OLS regressions of next-month excess returns on idiosyncratic volatility and the positive and negative one-month residual return components. Each column is a separate monthly cross-sectional regression. We report time-series average coefficients and t -statistics following the Newey–West procedure with automatic lag selection in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor. IVOL is the standard deviation of idiosyncratic returns ε over the formation month. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. All three measures skip the final formation-month trading day. In addition, RES^+ and RES^- also skip earnings announcements. We estimate idiosyncratic returns from the cross-sectional return decomposition in equation (3). The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. The sample period is January 1972–December 2022.

	Dependent variable: month $m + 1$ excess return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IVOL	−0.229 [−6.31]				0.255 [5.28]	−0.514 [−8.71]	0.005 [0.15]
RES^+		−0.055 [−11.58]		−0.064 [−12.56]	−0.079 [−11.38]		−0.064 [−12.39]
RES^-			−0.009 [−1.43]	−0.030 [−4.15]		−0.056 [−6.03]	−0.029 [−3.55]
Const.	0.014 [4.56]	0.020 [6.68]	0.004 [1.38]	0.014 [4.32]	0.017 [5.39]	0.010 [3.14]	0.014 [4.30]
R^2 (%)	7.2	7.3	7.3	7.8	7.5	7.6	7.8
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table D.3 uses $IVOL^{noEA}$, an alternative IVOL measure that excludes earnings-announcement-window days from the standard-deviation window in addition to the last day of the month. This addresses the concern that the headline IVOL measure mechanically loads on announcement-day return variance while the signed residual measures do not. $IVOL^{noEA}$ remains below conventional significance levels in every column once both signed residual components enter, and the slopes on RES^+ and RES^- are quantitatively close to the headline values.

Table D.3: Asymmetric reversal and idiosyncratic volatility with earnings-adjusted IVOL. The table reports Fama–MacBeth OLS and WLS regressions of next-month excess returns on idiosyncratic volatility and the positive and negative one-month residual return components. For WLS columns, we use market equity winsorized at the 80th NYSE percentile as the regression weight. Each column is a separate monthly cross-sectional regression. All columns use $IVOL^{noEA}$, the standard deviation of idiosyncratic returns ε over the formation month. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. All three measures skip the final formation-month trading day and also skip earnings announcements. We estimate idiosyncratic returns from the cross-sectional return decomposition in equation (3). We report time-series average coefficients and t -statistics following the Newey–West procedure with automatic lag selection in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor. The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. The sample period is January 1972–December 2022.

	Dependent variable: month $m + 1$ excess return			
	(1)	(2)	(3)	(4)
$IVOL^{noEA}$	0.024 [0.38]	0.073 [1.12]	0.071 [1.17]	0.114 [1.85]
RES^+	−0.067 [−7.66]	−0.068 [−7.09]	−0.070 [−11.05]	−0.073 [−10.23]
RES^-	−0.023 [−2.09]	−0.031 [−2.42]	−0.024 [−2.44]	−0.027 [−2.56]
Const.	0.012 [6.29]	0.009 [5.31]	0.015 [4.36]	0.014 [4.10]
R^2 (%)	3.1	3.2	7.9	9.7
Estimator	OLS	WLS	OLS	WLS
Controls	No	No	Yes	Yes

D.2 Raw-return sign components

Table D.4 compares raw-return and residual return sign components in the same one-month Fama–MacBeth design. Panel A shows that raw returns contain a visible sign asymmetry when entered alone: the contribution from positive raw-return days predicts stronger subsequent reversal than the contribution from negative raw-return

days. Panel B adds the signed residual components. Conditional on RES^+ and RES^- , the raw-return slopes are positive and their difference is statistically indistinguishable from zero across all four specifications. The residual return slopes remain negative in every specification, and the residual asymmetry is significant except in the WLS specification without controls. The evidence therefore points to signed residual pressure, rather than signed raw returns per se, as the object that carries the monthly asymmetry.

Table D.4: Raw-return and residual return sign components. The table reports Fama–MacBeth WLS and OLS regressions of next-month excess returns on signed one-month return components. Panel A includes the raw-return components RET^+ and RET^- ; Panel B adds RES^+ and RES^- from equation (3). RET^+ and RET^- are the sums of positive and negative daily raw returns over the formation month, respectively. RES^+ and RES^- are the sums of positive and negative residuals over the formation month, respectively. All four measures skip the final formation-month trading day and also skip earnings announcements. Columns (1) and (2) are WLS using market equity winsorized at the 80th NYSE percentile as weights; columns (3) and (4) are OLS. The set of controls in columns (2) and (4) includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. Difference rows report signed-component coefficient differences. We report time-series average coefficients and Newey–West t -statistics in brackets; boldface denotes statistical significance at the 95% confidence level. Coefficients are monthly excess-return slopes per unit of the displayed regressor, and R^2 is reported in percent. The sample period is January 1972–December 2022.

Dependent variable: month $m + 1$ excess return				
	(1)	(2)	(3)	(4)
<i>Panel A: Raw-return sign components</i>				
RET^+	−0.030 [−4.36]	−0.036 [−8.02]	−0.037 [−5.59]	−0.040 [−8.75]
RET^-	−0.006 [−0.72]	−0.014 [−2.12]	−0.001 [−0.15]	−0.013 [−2.00]
$RET^+ - RET^-$	−0.024 [−2.03]	−0.021 [−2.97]	−0.035 [−3.30]	−0.027 [−3.95]
R^2	4.82	10.31	3.99	8.16
LS	WLS	WLS	OLS	OLS
Controls	No	Yes	No	Yes
<i>Panel B: Raw-return and residual return sign components</i>				
RET^+	0.046 [4.16]	0.032 [3.75]	0.053 [4.97]	0.041 [4.72]
RET^-	0.058 [4.72]	0.037 [3.88]	0.068 [6.05]	0.043 [4.69]
RES^+	−0.103 [−9.33]	−0.093 [−8.80]	−0.112 [−10.18]	−0.100 [−9.45]
RES^-	−0.091 [−7.38]	−0.071 [−7.56]	−0.088 [−8.31]	−0.070 [−8.22]
$RET^+ - RET^-$	−0.011 [−0.94]	−0.005 [−0.53]	−0.014 [−1.33]	−0.003 [−0.34]
$RESdiff$	−0.012 [−1.19]	−0.023 [−2.63]	−0.024 [−2.44]	−0.030 [−3.42]
R^2	6.25	11.10	5.19	8.84
LS	WLS	WLS	OLS	OLS
Controls	No	Yes	No	Yes

E Short-term characteristic construction and diagnostics

E.1 Variable construction

This appendix describes the short-term characteristics used in the spanning tests. Table 5 summarizes their definitions, predicted return signs, and reference papers for each characteristic or economic channel. The spanning tests use across-stock variation in each characteristic to predict returns in the following month, conditional on the signed residual components and the controls used in the main monthly regressions.

Let m denote the portfolio-formation month and let returns in month $m + 1$ be the dependent variable. For daily CRSP variables, the baseline measure uses all valid daily observations in stock-month m . The one-day-skipped version excludes the final trading day of the formation month before aggregation, aligning the timing with the residual-reversal measures.

E.1.1 Low volatility

- $IVOL^{FF3}$. The benchmark IVOL variable follows [Ang et al. \(2006\)](#), who show that stocks with high recent idiosyncratic volatility earn low subsequent returns. [Hou and Loh \(2016\)](#) use this anomaly as the object to be explained by short-horizon candidate variables. For each stock-month, we estimate daily Fama-French three-factor residuals over month m and compute their standard deviation, requiring at least 10 daily observations. The one-day-skipped version repeats the same calculation after excluding the final trading day of the stock-month.
- *Ret Vol.* Return volatility is the total-return counterpart of IVOL and is part of the short-horizon volatility evidence in [Ang et al. \(2006\)](#). We compute the standard deviation of daily excess returns in month m , requiring at least 10 valid observations. The one-day-skipped version drops the final trading day before computing the standard deviation.

E.1.2 Lottery preferences

- *Skew.* Skewness is motivated by the lottery-demand channel in [Barberis and Huang \(2008\)](#), under which investors overpay for positively skewed payoffs. [Mitton and Vorkink \(2007\)](#) connect underdiversification and skewness preferences to the cross-section of returns, and [Bali et al. \(2016\)](#) discuss skewness as an

empirical return predictor. We compute the standardized third central moment of daily raw returns in the formation month, requiring at least 10 valid return days. The one-day-skipped version recomputes skewness after dropping the final trading day.

- $ISkew^{FF3}$. FF3 idiosyncratic skewness applies the same lottery-demand logic to idiosyncratic returns: positively skewed residual payoffs should be expensive and therefore predict lower subsequent returns. We use the idiosyncratic-skewness pricing evidence in [Mitton and Vorkink \(2007\)](#) and [Boyer et al. \(2010\)](#). We compute the standardized third central moment of daily Fama-French three-factor residuals in month m , requiring at least 10 valid residuals. The one-day-skipped version recomputes the FF3 residuals and skewness after dropping the final trading day.
- *Coskew*. Coskewness follows the conditional-coskewness asset-pricing evidence in [Harvey and Siddique \(2000\)](#). For returns predicted in month t , we residualize daily excess stock returns with respect to the excess market return in month $t - 1$ and compute the covariance between the stock residual and squared demeaned market excess returns, scaled by the stock residual volatility and squared market volatility. The one-day-skipped version removes the final trading day before residualization and aggregation.
- *MAX*. MAX is motivated by the lottery-demand evidence in [Bali et al. \(2011\)](#), who show that stocks with high maximum daily returns earn low subsequent returns. We compute the largest daily raw return in the formation month and require at least 10 valid return days. The one-day-skipped version recomputes the maximum after dropping the final trading day.
- *MAX5*. MAX5 is the average of the five largest daily raw returns in the formation month, following the lottery-demand measure in [Bali et al. \(2017\)](#). We require at least 10 valid return days. The one-day-skipped version recomputes the top-five average after dropping the final trading day.
- *SMAX*. SMAX follows [Asness et al. \(2020\)](#), who scale high maximum returns by volatility in testing lottery-like explanations for low-risk effects. We divide MAX5 by the standard deviation of daily excess returns over the trailing 252 trading days. The one-day-skipped version computes MAX5 after dropping the final trading day and uses the 252-day volatility ending on the previous trading day.

E.1.3 Liquidity

- *Lag Ret.* Lagged return captures the short-term reversal effect documented by [Jegadeesh \(1990\)](#). We sum daily excess returns over the formation month and require at least 10 valid return days. The one-day-skipped version excludes the final trading day of the formation month before summing.
- *Amihud.* Amihud illiquidity follows [Amihud \(2002\)](#), who show that illiquid stocks earn higher expected returns. [Han and Lesmond \(2011\)](#) and [Hou and Loh \(2016\)](#) use monthly liquidity measures, including Amihud-style price impact, in tests of whether trading frictions explain the IVOL-return relation. We compute the average of $|r_{i,d}|$ divided by dollar volume over formation-month days with valid returns and positive dollar volume, requiring at least 10 valid Amihud days. The one-day-skipped version drops the final trading day before aggregation.
- *Zero Trades.* Zero Trades follows the zero-return liquidity proxy in [Lesmond et al. \(1999\)](#) and the turnover-adjusted zero-volume-day measure in [Liu \(2006\)](#), which predicts returns through limited trading and illiquidity. [Han and Lesmond \(2011\)](#) use related zero-trading measures to study liquidity and expected returns. We compute the number of zero-volume days in the actual formation month plus inverse monthly turnover divided by 480,000. The measure is based on the actual number of observed days in the month, not a fixed 21-day standardization. The one-day-skipped version drops the final trading day before counting zero-volume days and forming monthly turnover.
- *Spread.* Spread captures the bid-ask spread compensation channel in [Amihud and Mendelson \(1986\)](#): stocks with higher trading costs should earn higher expected returns. We estimate the effective bid-ask spread using the high–low estimator of [Corwin and Schultz \(2012\)](#). [Hou and Loh \(2016\)](#) use bid-ask spreads as a trading-frictions explanation for IVOL. The monthly measure averages valid daily spread estimates in month m . The one-day-skipped version removes the final trading day before aggregation.
- *Turnover.* Turnover is average daily share turnover in month m . It is inspired by evidence that trading activity and share turnover predict returns at lower frequencies ([Lee and Swaminathan, 2000](#); [Datar et al., 1998](#); [Chordia et al., 2001](#)), but our short-horizon average is not a direct replication of these constructions. The one-day-skipped version averages daily share turnover after dropping the final trading day.

E.2 Replication and timing diagnostics

Two diagnostics check measurement and timing. Internet Appendix Table E.1 reports matched-sample correlations and average monthly means for characteristics with directly comparable benchmark measures. Internet Appendix Figure E.1 compares standalone t -statistics with and without the final trading day of the formation month.

Table E.1: Replication diagnostics for short-term characteristics. The table reports short-term characteristics with directly comparable benchmark measures. Average correlations are time-series averages of monthly cross-sectional correlations between the replicated characteristic using all formation-month observations and the target characteristic, shown in percent with one decimal place. The Replicated and Target columns first compute monthly cross-sectional means using matched stock-months with both variables observed, then average those monthly means over time. Difference is Replicated minus Target. Means use the same units as the spanning regressions and are displayed with three decimal places. Non-close analogues are omitted.

Characteristic	Months	Corr. (%)	Replicated	Target	Difference
IVOL ^{FF3}	612	99.5	0.019	0.020	-0.001
Ret Vol	612	100.0	0.024	0.024	0.000
Skew	612	100.0	0.002	0.002	0.000
ISkew ^{FF3}	612	95.1	0.001	0.002	0.000
Coskew	612	99.7	0.000	0.000	0.000
MAX	612	100.0	0.054	0.054	0.000
MAX5	612	99.6	0.031	0.031	0.000
SMAX	612	99.2	1.217	1.220	-0.003
Lag Ret	612	98.9	0.011	0.014	-0.003
Zero Trades	612	100.0	0.223	0.225	-0.003
Spread	612	97.9	0.009	0.009	0.000

Internet Appendix Table E.2 re-estimates the short-term characteristic spanning regressions over characteristic-specific reference windows. The table separates two issues. The full-sample tests in Table 6 ask whether the one-month characteristics contain incremental return predictability in our 1972–2022 sample. The overlap-window tests ask whether the same residual-spanning pattern is already visible in the historical samples that motivated the characteristics or their estimators. The table keeps characteristics with clear original-study or estimator windows and omits turnover because the one-month average daily turnover measure does not have a matching original-paper sample window.

Panel B shows that several standalone effects are stronger in their reference windows than in the full sample. IVOL, return volatility, MAX, MAX5, SMAX, and lagged returns enter with the conventional negative sign. FF3 idiosyncratic skewness is positive and significant, opposite to the lottery-preference prediction, whereas raw skewness is not significant. Amihud illiquidity, zero-trading days, and the Corwin–Schultz effective spread do not show reliable standalone premia in these controlled overlap regressions.

Panel C then adds RES^+ and RES^- . The residual components remain negative and significant across all columns. IVOL, return volatility, MAX5, Amihud, zero-trading days, and spread are insignificant after the residual controls. MAX, SMAX, and lagged return change sign, while the two skewness measures become positive. These estimates indicate that much of the return predictability in the one-month characteristics is tied to the signed residual return components, even when the tests are restricted to reference windows.

Table E.2: Short-term characteristic spanning regressions in overlap samples. The table reports Fama–MacBeth WLS regressions of next-month excess returns over characteristic-specific reference windows. Columns are characteristics with clear original-study or estimator windows; Turnover is not included. Panel A reports the first and last month of each overlap sample. Panel B reports standalone characteristic slopes. Panel C adds the positive and negative residual return components RES^+ and RES^- , which are the sums of positive and negative residuals over the formation month, respectively. They skip the final formation-month trading day and also skip earnings announcements. The set of controls includes: beta estimated over the previous 60 months; log of market equity; log book-to-market; operating profitability; asset growth; and prior 12-to-1-month momentum. All regressions use market equity winsorized at the 80th NYSE percentile as the regression weight. Characteristic definitions and reference papers are in Table 5. Skew, FF3 skewness, and coskewness are divided by 100, and Amihud is multiplied by 10^6 . Coefficients are time-series averages of monthly excess-return slopes. Newey–West t -statistics are reported in brackets; boldface denotes statistical significance at the 95% confidence level.

Variable	IVOL ^{FF3}	Ret Vol	Skew	ISkew ^{FF3}	Coskew	MAX	MAX5	SMAX	Lag Ret	Amihud	Zero Trades	Spread
<i>Panel A: Overlap windows</i>												
Start	1972-01	1972-01	1972-01	1988-01	1972-01	1972-01	1993-01	1972-01	1972-01	1972-01	1972-01	1972-01
End	2000-12	2000-12	2012-12	2005-12	1993-12	2005-12	2012-12	2015-12	1982-12	2012-12	2003-12	2006-12
<i>Panel B: Standalone regressions in overlap windows</i>												
Characteristic	−0.206	−0.160	0.040	0.121	0.168	−0.035	−0.113	−0.003	−0.047	−0.003	−0.001	−0.102
	[−4.55]	[−4.18]	[1.73]	[3.47]	[1.90]	[−3.03]	[−2.35]	[−5.43]	[−5.02]	[−1.26]	[−1.59]	[−1.09]
<i>Panel C: Spanning regressions in overlap windows</i>												
Characteristic	−0.044	0.045	0.177	0.223	0.170	0.079	0.089	0.003	0.047	−0.002	−0.000	0.029
	[−1.07]	[0.89]	[7.43]	[7.39]	[1.99]	[8.17]	[1.44]	[4.53]	[3.14]	[−0.70]	[−1.78]	[0.33]
RES^+	−0.079	−0.086	−0.077	−0.061	−0.088	−0.099	−0.063	−0.083	−0.143	−0.070	−0.079	−0.076
	[−13.81]	[−13.73]	[−14.76]	[−9.41]	[−15.71]	[−19.38]	[−7.91]	[−11.71]	[−10.69]	[−14.65]	[−16.24]	[−15.73]
RES^-	−0.060	−0.055	−0.049	−0.028	−0.065	−0.045	−0.020	−0.042	−0.131	−0.045	−0.053	−0.049
	[−8.17]	[−7.34]	[−5.77]	[−3.32]	[−7.20]	[−5.98]	[−2.07]	[−4.98]	[−10.87]	[−5.31]	[−6.71]	[−6.07]

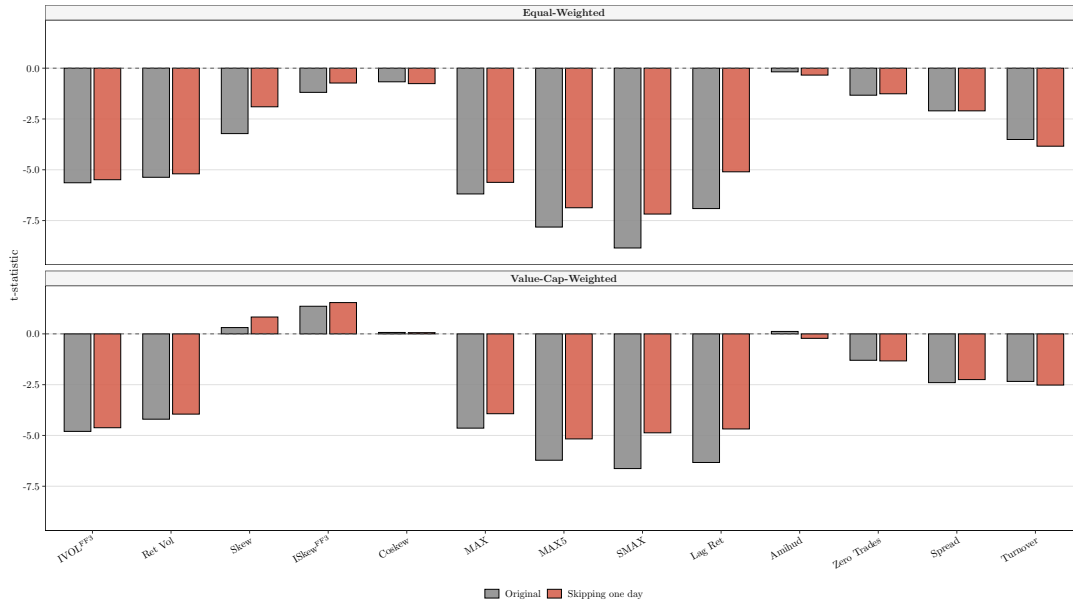


Figure E.1: Timing of short-term characteristics. This figure reports Fama–MacBeth t -statistics from standalone regressions of next-month excess returns on each characteristic. The horizontal axis lists the characteristics, and the vertical axis is the standalone return-predictability t -statistic; the dashed horizontal line marks zero. Gray bars are baseline characteristics that use all available observations in the formation month, and red bars are one-day-skipped characteristics that exclude the final trading day of the formation month. The top panel shows equal-weighted Fama–MacBeth estimates, and the bottom panel shows value-cap-weighted estimates. All regressions include the same controls as Table 6. Sample period: January 1972–December 2022.