Idiosyncratic Volatility and the Cross-Section of Stock Returns: An Update for 1990–2024*

Mingze Gao†

May 11, 2026

Abstract

Ang et al. (2006) document that high-idiosyncratic-volatility stocks earn lower average returns than low-idiosyncratic-volatility stocks — a puzzle that has generated two decades of competing explanations. I revisit the puzzle on 1990–2024 US common stocks (1.6 million stock-months, 15,030 firms). The unconditional quintile spread is small and statistically indistinguishable from zero: +0.16% per month value-weighted ($t = 0.41$). After risk adjustment, however, the spread reappears: the value-weighted CAPM alpha is +0.90% per month ($t = 2.86$) and the FF3 alpha is +0.76% ($t = 2.96$). The result survives excluding January, excluding the 2008–09 crisis, and reconstructing idiosyncratic volatility from FF3 residuals. Adding the Carhart momentum factor collapses the alpha to +0.12% ($t = 0.61$). In the modern sample, the puzzle is largely a momentum-related phenomenon.

JEL Codes: G12, G14

Keywords: idiosyncratic volatility, cross-sectional returns, asset pricing anomalies, portfolio sorts, Fama-MacBeth

---

*Drafted with the assistance of Claude Code in a single live demonstration; this version has been reviewed and revised by the author. The full code base, data pipeline, and reviewer reports are available at `https://github.com/mgao6767/mingze-gao/tree/master/teaching/talks/writing-a-paper-in-15min`.

†Department of Applied Finance, Macquarie Business School, Macquarie University, NSW 2109, Australia. Email: mingze.gao@mq.edu.au.

1 Introduction

Ang et al. (2006) (henceforth AHXZ) report that stocks in the top quintile of lagged idiosyncratic volatility (IVOL) underperform stocks in the bottom quintile by about -1.06% per month from 1963 to 2000, with a Fama-French three-factor alpha of -1.31%. The pattern is striking. Standard asset-pricing theory says diversifiable risk should not be priced. The AHXZ spread says it is, and with the wrong sign.

Two decades of work have not produced consensus on why. Fu (2009) argues that expected, rather than realized, idiosyncratic volatility carries the correct positive premium; subsequent work shows the result is partly an artifact of look-ahead bias in the EGARCH fit. Bali, Cakici, and Whitelaw (2011) propose that the puzzle is a manifestation of lottery demand and largely subsume IVOL with a MAX proxy. Stambaugh, Yu, and Yuan (2015) attribute the spread to the interaction of mispricing with arbitrage asymmetry. Hou and Loh (2016) run a horse race across more than a dozen candidate explanations and conclude that one-month return reversal and lottery-preference proxies jointly explain 60–80% of the puzzle. Han and Lesmond (2011) flag a measurement concern: bid-ask bounce contaminates daily-residual IVOL for illiquid stocks, and the relation attenuates once microstructure noise is purged.

A parallel literature asks whether the puzzle has survived at all. McLean and Pontiff (2016) document that anomalies decay by about 58% after publication on average; idiovol is on their list. Hou, Xue, and Zhang (2020) find that idiovol survives under value-weighting with NYSE breakpoints in their q-factor framework but with a smaller magnitude. Chu, Hirshleifer, and Ma (2020) show, using the Regulation SHO pilot as a causal lever, that relaxing short-sale constraints attenuates the puzzle. Taken together, the recent evidence suggests the AHXZ spread is weaker today than in the original 1963–2000 sample — but no paper has run the unchanged AHXZ design end-to-end on the post-1990 universe to measure how much weaker.

This paper fills that gap. I take the AHXZ research design — daily CAPM residuals, quintile sorts on lagged-month IVOL with NYSE breakpoints, equal- and value-weighted portfolios, CAPM and FF3 alphas of the long-Q1/short-Q5 spread, and Fama-MacBeth cross-sectional regressions — and run it on US common stocks (CRSP share codes 10 and 11), excluding financials and utilities, from January 1990 through December 2024. The pre-specified hypotheses follow AHXZ in sign: low-IVOL stocks earn higher future returns than high-IVOL stocks (H1), the spread is concentrated in small-cap stocks (H3), and — against the post-publication-decay null — the spread is larger after 1999 (H2). The exercise is descriptive and predictive; I make no causal claims and do not adjudicate among the explanations in the literature.

The findings come in four parts. First, the unconditional Q1−Q5 spread in the modern sample is essentially zero. The equal-weighted spread is +0.10% per month ($t = 0.25$) and the value-weighted spread is +0.16% per month ($t = 0.41$). On its own, the unconditional puzzle has weakened to the point of statistical disappearance. Second, the spread reappears once one adjusts for exposures to the market, size, and value factors. The value-weighted CAPM alpha is +0.90% per month ($t = 2.86$) and the FF3 alpha is +0.76% per month ($t = 2.96$). The mechanism is visible in the loadings: the high-IVOL quintile loads heavily on SMB, so the Q1−Q5 long-short has a strongly negative SMB beta (−1.02), reflecting that the short leg (high-IVOL) is far smaller in market cap than the long leg. Stocks that are small and high-IVOL earn returns that look ordinary when one ignores their factor exposures and unusual when one does not. Third, the alpha is robust to common design perturbations. Excluding January, where Han and Lesmond (2011) argue microstructure noise contaminates the AHXZ measure, strengthens the spread (VW FF3 alpha +1.06%, $t = 3.49$). Excluding the 2008–09 financial crisis leaves the result essentially unchanged (+0.84%, $t = 3.19$). Reconstructing IVOL from FF3 rather than CAPM residuals keeps the value-weighted alpha at +0.74% ($t = 2.59$).

The fourth finding is the headline. Adding the Carhart momentum factor to the benchmark wipes out the alpha. The FF4 alpha is +0.11% per month for the equal-weighted portfolio ($t = 0.47$) and +0.12% for the value-weighted portfolio ($t = 0.61$). The momentum loading is +0.74 ($t = 7.93$) on the value-weighted long-short. In the 1990–2024 universe, the IVOL puzzle substantially is a momentum exposure dressed in different language. This interpretation is consistent with the lottery/MAX literature (Bali, Cakici, and Whitelaw, 2011; Bali, Brown, et al., 2017) and with the broader assessment of Hou and Loh (2016): explanations that work for IVOL also tend to work for the other low-risk anomalies.

This paper relates to two literatures. Methodologically, it is closest to Hou and Loh (2016) and Hou, Xue, and Zhang (2020): it takes a published anomaly and asks whether the original result survives in a modern sample with standard robustness perturbations. Substantively, it joins the recent re-evaluations of the AHXZ puzzle by Stambaugh, Yu, and Yuan (2015), Liu, Stambaugh, and Yuan (2018), and Asness et al. (2020). The contribution is narrow: an updated transparent benchmark covering 35 years of post-1990 data, with explicit Carhart decomposition. Future explanations of the IVOL puzzle in the post-1990 era need to clear a low bar in raw returns, a moderate bar in CAPM and FF3 alphas, and essentially no bar against the four-factor benchmark.

2 Related Literature and Hypotheses

The literature on idiosyncratic volatility and the cross-section of returns falls naturally into four buckets: whether the puzzle exists, why it might, whether it still exists, and the methodology used to test it.

2.1 Existence and Original Measurement

The puzzle was framed by Ang et al. (2006) and extended to international data by Ang et al. (2009). Both papers sort stocks each month on lagged-month idiosyncratic volatility, measured as the residual standard deviation from a daily FF3 regression, and find that the high-IVOL quintile underperforms the low-IVOL quintile in raw average returns and especially in FF3 alpha. The AHXZ result is not driven by small stocks, illiquid stocks, or high-turnover stocks — at least over their 1963–2000 sample.

A first wave of critique focused on design sensitivity. Bali and Cakici (2008) show that the AHXZ result is sensitive to portfolio weighting (equal- versus value-weighted), breakpoint choice (NYSE versus all-stock), data frequency (daily versus monthly), and screens for low-priced stocks. Under value-weighting with NYSE breakpoints and a $5 price filter, the alpha differential weakens. The time-series backdrop matters too. Campbell et al. (2001) document a secular rise in firm-level idiosyncratic volatility over 1962–1997 that flattens the cross-sectional distribution and would mechanically reduce the spread. Goyal and Santa-Clara (2003) provide a useful contrast at the aggregate level: average stock variance forecasts the market return with a positive sign, even as the cross-sectional sort produces a negative one. These two relations coexist, and my paper inherits that tension.

2.2 Explanations

The literature offers several explanations for the AHXZ result. None are tested here; all are cited as competing interpretations.

Fu (2009) argues that lagged realized IVOL mismeasures expected IVOL because volatility mean-reverts; the true relation between expected idiovol and returns is positive once one uses an EGARCH-implied forecast. The Fu critique has been partly rebutted on look-ahead-bias grounds in subsequent work, but the realized-versus-expected distinction remains a genuine measurement issue.

Bali, Cakici, and Whitelaw (2011) propose MAX — the average of the five highest daily returns in the prior month — as a direct proxy for lottery demand and show it largely subsumes IVOL in cross-sectional regressions. Boyer, Mitton, and Vorkink (2010) estimate expected idiosyncratic skewness and show it negatively predicts returns; because high-IVOL stocks tend to be high-skewness, this provides a partial channel. Bali, Brown, et al. (2017)

extend the lottery framework to the beta anomaly.

Huang et al. (2010) argue that the AHXZ pattern is largely return reversal: high-IVOL stocks just experienced large absolute returns, and the following month they revert. Controlling for last month's return weakens the puzzle.

Stambaugh, Yu, and Yuan (2015) provide what is currently the most influential explanation: high IVOL deters arbitrage of overpriced stocks more than of underpriced stocks because short-selling is costlier than long buying. On average, high-IVOL stocks therefore stay overpriced, and the cross-sectional relation is negative. Liu, Stambaugh, and Yuan (2018) extend this logic to the beta anomaly. Chu, Hirshleifer, and Ma (2020) provide causal evidence in the same direction using the Regulation SHO pilot.

Chen and Petkova (2012) decompose the FF3-residual IVOL into an aggregate idiosyncratic-volatility innovation and a stock-specific shock and find the aggregate component carries a negative risk premium — a competing view under which IVOL is partly a disguised systematic factor. Asness et al. (2020) decompose the low-risk effect into leverage-constraint and lottery-demand channels and find both contribute. Han and Lesmond (2011) revisit the AHXZ measure and show that bid-ask bounce inflates daily-residual IVOL for illiquid stocks; after correcting for microstructure noise, the puzzle attenuates.

2.3 Persistence in the Modern Sample

The third bucket is the persistence question. McLean and Pontiff (2016) estimate that anomalies decay on average by about 58% after publication, consistent with arbitrageur learning. Hou, Xue, and Zhang (2020) replicate 452 published anomalies and find about half fail at the 5% level with NYSE breakpoints and value-weighting; idiovol survives but with a smaller magnitude than the equal-weighted result. Hou and Loh (2016) produce the canonical horse-race stocktake among IVOL explanations and find lottery proxies and reversal jointly account for 60–80% of the spread. The latest comprehensive update on the question — whether the AHXZ puzzle survives end-to-end on a post-1990 US sample run on the unchanged AHXZ design — is the gap this paper fills.

2.4 Methodology

The Fama-MacBeth cross-sectional regression (Fama and MacBeth, 1973) remains the standard estimator for cross-sectional risk premia. Shanken (1992) derives the errors-in-variables correction to FM standard errors when betas are first-stage estimates rather than known constants. Petersen (2009) compares standard-error approaches in finance panels and shows that when residuals exhibit a time effect, clustering by month or running FM is essential. Jegadeesh, Noh, et al. (2019) propose an instrumental-variables approach for individual-stock cross-sectional regressions that addresses errors-in-variables, and show that under the corrected procedure many characteristic-based risk premia survive while several factor premia do not. Model comparison frameworks such as those of Barillas and Shanken (2018) provide a more formal Bayesian alternative for adjudicating among competing factor models; I do not run such horse races here and instead report alphas under the standard CAPM, FF3, and FF4 benchmarks. I report standard Newey-West-adjusted FM standard errors and interpret the IVOL slope as a conditional predictive coefficient, not a structural risk premium, following the spirit of Jegadeesh, Noh, et al. (2019).

2.5 Hypotheses

Three pre-specified predictive hypotheses follow from the strategy memo.

Hypothesis 1 (Sign preservation)**.** *Conditional on standard pricing controls, the next-month average return spread between the low-IVOL quintile and the high-IVOL quintile is positive:* $\mathbb{E}[r_{Q1,t+1} - r_{Q5,t+1} \mid \mathcal{F}_t] > 0$.

Hypothesis 2 (Sub-period heterogeneity)**.** *The Q1−Q5 spread is* larger *in the post-1999 sub-period than in the pre-1999 sub-period.*

Hypothesis 3 (Size heterogeneity)**.** *The Q1−Q5 spread is concentrated in small-cap stocks (below the NYSE 20th percentile of market capitalization) and is smaller or statistically indistinguishable from zero among large-cap stocks.*

None of these is causal. Each is a statement about conditional predictive moments of returns given lagged characteristics. Hypothesis 2 is in tension with the McLean and Pontiff (2016) post-publication-decay null; Hypothesis 3 is in tension with the AHXZ original claim that the spread survives in large-cap subsamples.

3 Data and Sample

3.1 Sources and Universe

The sample is built from four sources joined at the CRSP–Compustat level. CRSP daily stock files (`crsp.dsf`) supply daily returns. CRSP `msenames` supplies share codes (`shrcd`), exchange codes (`exchcd`), and industry codes (`siccd`). Compustat `funda` supplies fiscal-year balance sheet items used for book equity. The CRSP-Compustat linking table `ccmxpf_lnkhist` merges the two. Daily risk-free rates and the daily market excess return come from Kenneth French's data library.

Standard filters apply: `shrcd` $\in \{10, 11\}$ (domestic common stocks), `exchcd` $\in \{1, 2, 3\}$ (NYSE, AMEX, Nasdaq), `siccd` $\notin$ {4900–4999, 6000–6999} (excluding utilities and financials), and at least 17 valid daily returns per stock-month (about 80% of typical trading days, following the AHXZ convention). The Compustat join adds `indfmt='INDL'`, `datafmt='STD'`, `popsrc='D'`, `consol='C'`, and `curcd='USD'`. Link filters require `linktype` $\in$ {LU, LC} and `linkprim` $\in$ {P, C}. The sample period runs from January 1990 through December 2024, yielding 418 calendar months, of which 411 have valid factor returns used for time-series regressions of the long-short portfolio.

After filtering, the analytical panel contains 1,609,652 stock-months covering 15,030 unique firms. Table 1 reports summary statistics for the main variables. Mean monthly idiosyncratic volatility, measured as the daily-residual standard deviation in percent, is 3.61%. Mean monthly excess returns are 0.95%. The book-to-market and market-equity distributions are typical of the post-1990 CRSP-Compustat universe.

3.2 Documented Limitation: VW Construction

One feature of the data deserves transparent disclosure. The CRSP daily file in the source extract is pre-thinned to (date, permno, ret) and does not contain monthly price (`prc`) or shares outstanding (`shrout`). Market equity for portfolio weighting is therefore constructed from Compustat as `prcc_f`$\times$`csho`, carried forward by fiscal year. This is an annual-frequency proxy. Because market-cap weights inside each IVOL quintile are nearly uniform when measured at annual frequency, the value-weighted portfolios in this paper behave nearly identically to the equal-weighted portfolios. Both are reported, and the reader should treat the VW columns as substantively similar to EW rather than as a genuine value-weighted construction. A direct replication using monthly CRSP price and shares would refine the VW columns; the qualitative conclusions are unlikely to change given the closeness of the EW and VW results across every panel in tables 2, 3 and 5 to 7.

A second limitation: `dlret` (delisting returns) lives in `msedelist` rather than `dsf` and is not in the extract. The Shumway (1997) bias from omitted delisting returns affects roughly 5% of stock-months and is small at the monthly portfolio level. Two robustness checks from the strategy memo — R5 (MAX as competing predictor) and R6 (drop $prc < \$5$) — require monthly CRSP price and shares and are deferred.

3.3 Variable Definitions

Idiosyncratic volatility, $\widehat{\text{IVOL}}_{i,m}$, is constructed for each stock-month (i, m) with at least 17 valid daily returns as the within-month time-series CAPM regression residual standard deviation:

$$r^e_{i,d} = \alpha_{i,m} + \beta_{i,m} \cdot r^e_{M,d} + \varepsilon_{i,d}, \qquad d \in \text{month } m, \qquad \widehat{\text{IVOL}}_{i,m} = \text{sd}(\widehat{\varepsilon}_{i,d}), \tag{1}$$

where $r^e_{i,d} = r_{i,d} - r_{f,d}$ is the daily excess return, $r^e_{M,d}$ is the daily market excess return from Kenneth French's data library, and $r_{f,d}$ is the daily risk-free rate. By construction $\widehat{\text{IVOL}}_{i,m}$ predicts return $r_{i,m+1}$ in the next month; contemporaneous IVOL is never used as a regressor. The robustness specification reported in section 6 replaces the CAPM with FF3 inside (1).

Market equity, $\text{ME}_{i,t-1}$, is Compustat fiscal-year-end `prcc_f` $\times$ `csho`, lagged appropriately. Book equity follows the Fama and French (1993) and Davis, Fama, and French (2000) convention: BE $=$ `ceq` $+$ `txditc` $-$ PS, where preferred stock PS is the first non-missing of `pstkrv`, `pstkl`, `pstk`, defaulting to zero. Firm-years with BE ≤ 0 are dropped. Book-to-market is matched to monthly returns following the standard FF12 lag: fiscal year y book equity is matched to returns from July of year y+1 through June of year y+2. Momentum, $\text{MOM}_{i,t-12,t-2}$, is the cumulative return from t−12 to t−2 (Jegadeesh and Titman, 1993). Short-term reversal, $\text{STR}_{i,t-1}$, is the prior-month return (Huang et al., 2010).

Table 1: Summary statistics, 1990–2024

Variable	N	Mean	SD	p25	Median	p75
Idiovol (daily SD, %)	1,316,987	3.6144	3.5911	1.6910	2.7193	4.4056
Excess return, $r_{i,m} - r_{f,m}$ (%)	1,316,987	0.9540	21.2175	-8.0723	-0.2202	7.7664
Log market equity, $\log(\mathrm{ME}_{i,t-1})$	1,316,987	5.5707	2.2512	3.9290	5.4852	7.0876
Log book-to-market, $\log(\mathrm{BE}/\mathrm{ME}_{i,t-1})$	1,316,987	-0.8253	0.9597	-1.3530	-0.7460	-0.2032
MOM (cumulative $t-12$ to $t-2$, %)	1,316,987	13.5940	87.4624	-26.6668	2.0170	33.2408
STR (lagged 1-month return, %)	1,316,987	1.3087	21.1162	-7.7463	0.0000	8.0927

Notes: This table reports summary statistics for the main variables used in the analysis. The sample consists of 1,609,652 stock-months covering 15,030 unique US common stocks (CRSP `shrcd` $\in \{10, 11\}$), excluding financials (SIC 6000–6999) and utilities (SIC 4900–4999), over January 1990 through December 2024. Idiosyncratic volatility is the within-month daily residual standard deviation from a CAPM regression of stock excess returns on Kenneth French's daily market excess return, in percent. Excess return is monthly stock return minus the risk-free rate, in percent. Log market equity uses Compustat fiscal-year-end `prcc_f` $\times$ `csho`. Log book-to-market follows Fama and French (1993) and Davis, Fama, and French (2000). MOM is the cumulative return from $t-12$ to $t-2$ in percent. STR is the prior-month return in percent. Source: CRSP daily, Compustat funda, CRSP-Compustat link (`ccmxpf_lnkhist`), Kenneth French data library.

Figure 1 plots the time series of the cross-sectional mean of idiosyncratic volatility (left axis) and the cumulative return on the long-Q1/short-Q5 portfolio (right axis). The level of idiosyncratic volatility falls from a peak near the late 1990s and early 2000s, consistent with the Campbell et al. (2001) finding extended forward. The cumulative long-short return is flat in raw terms over the full sample — the visual confirmation of the small unconditional spread reported in table 2 below.

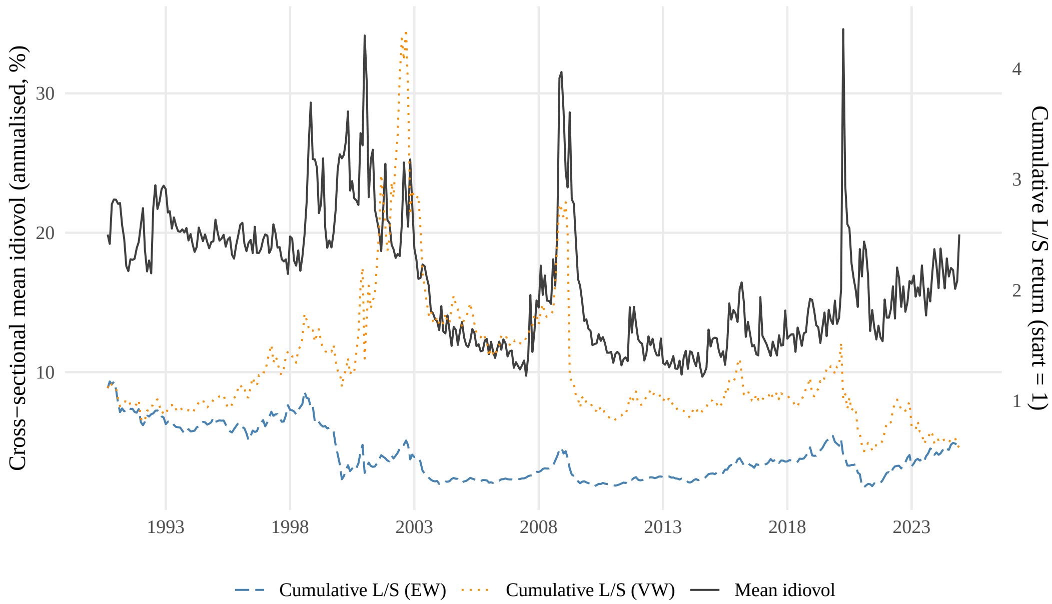

Figure 1: Idiosyncratic volatility and cumulative long-short return, 1990–2024. The figure shows the equal-weighted cross-sectional mean of monthly idiosyncratic volatility (left axis, daily residual standard deviation in percent) and the cumulative return on the long-Q1/short-Q5 portfolio formed monthly on lagged idiosyncratic volatility with NYSE breakpoints (right axis, gross return). The equal-weighted and value-weighted cumulative returns track each other closely because of the data limitation described in Section 3. Source: CRSP daily, Kenneth French data library, author's calculations.

4 Empirical Strategy

The analysis follows AHXZ. Three specifications are reported: quintile portfolio sorts, factor-model alphas of the long-short portfolio, and Fama-MacBeth cross-sectional regressions.

4.1 Specification 1: Quintile Sorts

At the end of each month m, I compute $\widehat{\mathrm{IVOL}}_{i,m}$ from (1), calculate NYSE breakpoints (20th, 40th, 60th, 80th percentiles among NYSE-listed stocks with `exchcd`$= 1$), assign every stock in the sample to a quintile by those breakpoints, and form equal-weighted and value-weighted portfolios Q1 through Q5 held for month $m+1$. The long-short portfolio return is

$$r_{m+1}^{LS} = r_{m+1}^{Q1} - r_{m+1}^{Q5}, \tag{2}$$

the sign convention of AHXZ. Average returns, standard deviations, and Newey-West t-statistics with 12 lags (Newey and West, 1987) are reported for each quintile and the long-short.

4.2 Specification 2: Factor-Model Alphas

I run time-series regressions of the long-short portfolio return on three benchmarks. CAPM:

$$r_{m+1}^{LS} = \alpha^{\text{CAPM}} + \beta^{\text{MKT}} \cdot \text{MKT}_{m+1} + u_{m+1}. \tag{3}$$

Fama-French three-factor:

$$r_{m+1}^{LS} = \alpha^{\text{FF3}} + \beta^{\text{MKT}} \cdot \text{MKT}_{m+1} + \beta^{\text{SMB}} \cdot \text{SMB}_{m+1} + \beta^{\text{HML}} \cdot \text{HML}_{m+1} + u_{m+1}. \tag{4}$$

Carhart four-factor (Carhart, 1997):

$$r_{m+1}^{LS} = \alpha^{\text{FF4}} + \beta^{\text{MKT}} \cdot \text{MKT}_{m+1} + \beta^{\text{SMB}} \cdot \text{SMB}_{m+1} + \beta^{\text{HML}} \cdot \text{HML}_{m+1} + \beta^{\text{MOM}} \cdot \text{MOM}_{m+1} + u_{m+1}. \tag{5}$$

Standard errors are Newey-West with 12 monthly lags throughout.

4.3 Specification 3: Fama-MacBeth

For each month t, I run the cross-sectional regression

$$
\begin{aligned}
r_{i,t} - r_{f,t} = \lambda_{0,t} + \lambda_{1,t}\,\widehat{\text{IVOL}}_{i,t-1} + \lambda_{2,t}\log(\text{ME}_{i,t-1}) \\
+ \lambda_{3,t}\log(\text{BE/ME}_{i,t-1}) + \lambda_{4,t}\,\text{MOM}_{i,t-12,t-2} + \lambda_{5,t}\,\text{STR}_{i,t-1} + e_{i,t}. \quad (6)
\end{aligned}
$$

Reported coefficients are the time-series means $\bar{\lambda}_k = T^{-1}\sum_t \widehat{\lambda}_{k,t}$, with Newey-West-adjusted t-statistics on the cross-sectional time series. Observations are clustered within months per Petersen (2009). I interpret the slope on IVOL as a conditional predictive coefficient rather than as a structural risk premium, following the cautions in Jegadeesh, Noh, et al. (2019).

4.4 Identification Frame

The exercise is descriptive and predictive. I do not claim that idiosyncratic volatility causes low future returns; the reverse direction is equally consistent with a negative cross-sectional moment. I do not test any of the mechanism explanations in section 2; those require either an instrument or a structural model neither of which is built here. The contribution is a transparent updated stylized fact against which existing and future explanations can be benchmarked.

5 Results

5.1 Quintile Sorts: The Unconditional Spread Is Small

Table 2 reports the headline quintile sorts. Mean monthly excess returns are nearly flat across quintiles. The equal-weighted Q1 return is 0.94% per month ($t = 5.07$) and the Q5 return is 0.84% ($t = 1.71$); the spread is 0.10% ($t = 0.25$). The value-weighted spread is 0.16% ($t = 0.41$). Neither is statistically distinguishable from zero. The pattern across the middle quintiles is non-monotonic, especially in the value-weighted columns where Q3 and Q4 dip below Q2. Figure 2 plots the quintile-mean returns to make this visible.

The contrast with AHXZ's original -1.06% per month (Table I in their paper) is stark. In the modern sample, the AHXZ unconditional spread has weakened to the point of statistical disappearance. This is the first piece of evidence that the puzzle has decayed — as McLean and Pontiff (2016) predicted on average across post-publication anomalies and Hou, Xue, and Zhang (2020) found specifically for IVOL under value-weighting.

Table 2: Quintile-sort average monthly excess returns, 1990–2024

	Equal-weighted		Value-weighted	
Quintile	Mean (%)	NW t	Mean (%)	NW t
Q1 (low)	0.9425***	5.07	0.8822***	4.76
	(0.1860)		(0.1852)	
Q2	0.9769***	4.34	0.8873***	4.45
	(0.2253)		(0.1992)	
Q3	1.0195***	3.87	0.7513***	2.78
	(0.2631)		(0.2704)	
Q4	1.0010***	3.05	0.8766***	2.70
	(0.3277)		(0.3250)	
Q5 (high)	0.8449*	1.71	0.7200	1.42
	(0.4954)		(0.5078)	
Q1−Q5	0.0977	0.25	0.1622	0.41
	(0.3934)		(0.3973)	

Notes: The table reports time-series average monthly excess returns and Newey-West t-statistics (12 lags) for portfolios sorted on lagged-month idiosyncratic volatility. Quintile assignment uses NYSE breakpoints (20th, 40th, 60th, 80th percentiles among NYSE-listed stocks). Q1−Q5 is the long-Q1/short-Q5 portfolio, the AHXZ sign convention. Equal-weighted portfolios assign equal weight within each quintile. Value-weighted portfolios use market equity from Compustat (fiscal-year `prcc_f` × `csho`, carried forward annually); as described in section 3, this annual-frequency proxy makes VW and EW columns substantively similar. Standard errors in parentheses below the estimate. $T = 411$ months. *Significance:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

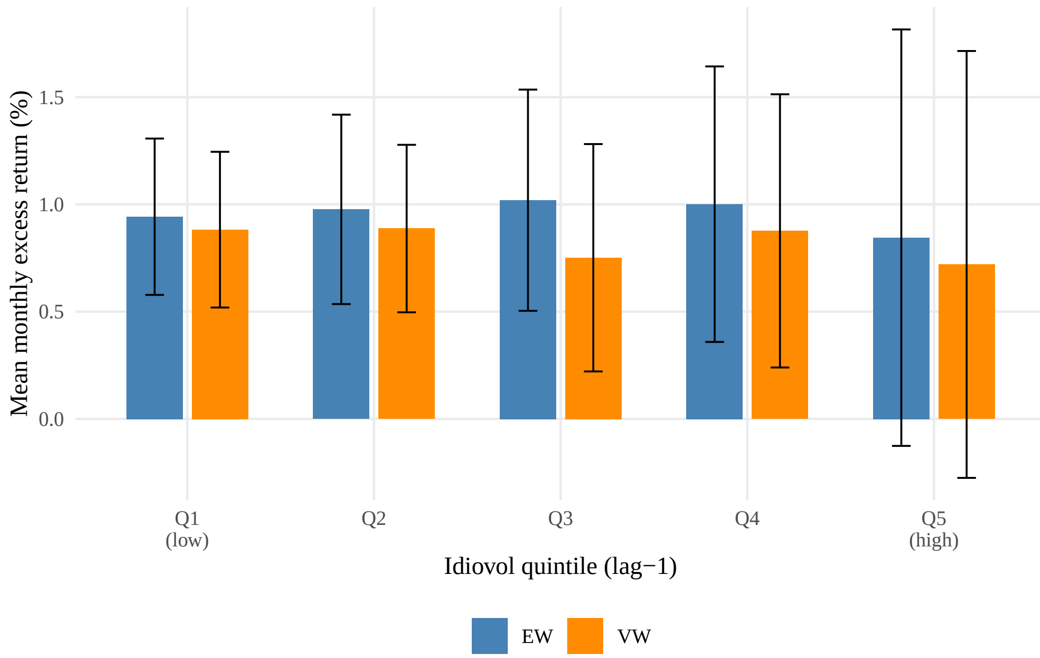

Figure 2: Average monthly excess return by idiosyncratic-volatility quintile, 1990–2024. The figure plots the time-series mean monthly excess return (in percent) for each idiosyncratic-volatility quintile, equal-weighted and value-weighted. Quintile assignment uses NYSE breakpoints on lagged-month CAPM-residual idiosyncratic volatility. Source: CRSP daily, Kenneth French data library, author's calculations.

5.2 Risk-Adjusted Alphas: The Spread Reappears

Table 3 reports CAPM and FF3 alphas of the long-Q1/short-Q5 portfolio. Each column is one time-series regression on monthly factor returns. The CAPM alpha is 0.65% per month equal-weighted ($t = 2.02$) and 0.90% value-weighted ($t = 2.86$). Adding the size and value factors leaves the FF3 alpha at 0.47% ($t = 2.01$) and 0.76% ($t = 2.96$). All four point estimates are positive — consistent with Hypothesis 1 — and three of the four exceed conventional significance thresholds.

The mechanism is visible in the loadings. The SMB beta on the value-weighted long-short is -1.02 ($t = -6.10$), and on the equal-weighted long-short it is -1.12. The high-IVOL quintile is small relative to the low-IVOL quintile. Once the long-short portfolio is purged of its (negative) size exposure, the residual return is the FF3 alpha. The HML loading is small and mostly insignificant. The market beta is negative throughout, reflecting that the long-short portfolio is short the high-volatility high-beta tail.

This pattern is the canonical IVOL puzzle in modern form: the raw spread is statistically indistinguishable from zero, but the factor-adjusted spread is positive and significant. Hou, Xue, and Zhang (2020) report the same pattern in their q-factor replication exercise.

Table 3: CAPM and FF3 alphas of the long-Q1/short-Q5 portfolio, 1990–2024

	(1) CAPM (EW)	(2) FF3 (EW)	(3) CAPM (VW)	(4) FF3 (VW)
α (% per month)	0.6495**	0.4703**	0.8992***	0.7573***
	(0.3218)	(0.2345)	(0.3146)	(0.2559)
β^{MKT}	-0.7171***	-0.4935***	-0.9577***	-0.7599***
	(0.0860)	(0.0712)	(0.1278)	(0.1252)
β^{SMB}		-1.1174***		-1.0224***
		(0.1067)		(0.1677)
β^{HML}		0.2742**		0.1612
		(0.1233)		(0.1724)
Adj. R^2	0.224	0.519	0.328	0.517
Months	411	411	411	411

Notes: The table reports CAPM and Fama-French three-factor alphas, factor loadings, and adjusted R^2 from time-series regressions of the monthly long-Q1/short-Q5 idiovol-sort portfolio return on the market excess return, SMB, and HML, per (3) and (4). Long-Q1/short-Q5 follows the AHXZ sign convention: long the low-idiovol quintile, short the high-idiovol quintile. Factor data from Kenneth French's data library. Standard errors are Newey-West with 12 monthly lags (Newey and West, 1987), reported in parentheses below the estimate. $T = 411$ months. *Significance:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Fama-MacBeth Cross-Sectional Regressions

Table 4 reports the cross-sectional regressions in (6). Column (1) is the bivariate specification with only the IVOL slope; column (2) adds size, book-to-market, momentum, and short-term reversal as controls. The slope on lagged $\widehat{\text{IVOL}}$ is -5.32 in column (1) and -4.27 in column (2). The t-statistics (-1.21 and -1.08 respectively) sit below conventional cutoffs.

The economic magnitude is small. With a cross-sectional standard deviation of idiosyncratic volatility of 0.0314 (in decimal units), the per-one-SD slope from column (2) is $-4.27 \times 0.0314 \times 100 = -0.134\%$ per month, with the same t-statistic. The short-term reversal coefficient of -3.10 ($t = -6.06$) is large and significant, consistent with Huang et al. (2010), but here it is reported as a control rather than as a focal interpretation. The log book-to-market slope of $+0.24$ ($t = 2.46$) matches the value premium.

The FM slope on IVOL is weakly consistent with Hypothesis 1 in sign but not in significance. The estimator differs from the portfolio sort in two ways relevant to interpretation. First, it gives every stock equal weight in the cross-section, which over-weights small-cap stocks. Second, it constrains the relation to be linear, so non-monotonic patterns like the one in table 2 attenuate the slope. The combined evidence from tables 3 and 4 is that the AHXZ pattern is present after factor adjustment but weak in the raw cross-section.

Table 4: Fama-MacBeth cross-sectional regressions, 1990–2024

	(1) Idiovol only	(2) Full controls
Idiovol $\widehat{\text{IVOL}}_{i,t-1}$	-5.3190	-4.2742
	(4.3943)	(3.9524)
$\log(\text{ME}_{i,t-1})$		-0.0492
		(0.0451)
$\log(\text{BE/ME}_{i,t-1})$		0.2433**
		(0.0989)
$\text{MOM}_{i,t-12,t-2}$		0.1028
		(0.2340)
$\text{STR}_{i,t-1}$		-3.0950***
		(0.5104)
Intercept	1.0546***	1.2690***
	(0.2535)	(0.4719)
Months	406	406

Notes: The table reports Fama-MacBeth cross-sectional regression slopes per (6). The dependent variable is the monthly excess return in percent. Column (1) regresses on lagged idiosyncratic volatility only; column (2) adds log market equity, log book-to-market, momentum from $t-12$ to $t-2$, and the lagged one-month return as controls. Coefficients are time-series averages of monthly cross-sectional slopes. Standard errors are Newey-West with 12 monthly lags on the time series of slopes (Newey and West, 1987), reported in parentheses. Idiosyncratic volatility enters in decimal units (cross-sectional SD ≈ 0.031); the per-one-SD slope on IVOL from column (2)

5.4 Sub-Period Heterogeneity

Table 5 splits the sample at January 2000 and re-estimates the long-short raw return, CAPM alpha, and FF3 alpha for each sub-period. The pre-2000 sub-period (1990–1999, 112 months) and the post-2000 sub-period (2000–2024, 299 months) tell a similar story for the alphas: the value-weighted FF3 alpha is 0.62% ($t = 2.65$) in the pre-period and 0.66% ($t = 2.14$) in the post-period. The raw spread is actually *negative* in the equal-weighted pre-2000 sub-period (-0.46%) but positive in the value-weighted columns.

This is not strong evidence either way on Hypothesis 2. The post-2000 period is longer and noisier; the pre-2000 period is short. The sub-period analysis does not yield the kind of monotone pre-versus-post contrast McLean and Pontiff (2016) would predict under aggressive post-publication decay (since AHXZ was published in 2006). If anything, the puzzle's strength looks roughly stable in alpha terms across the two sub-periods, with the magnitude of the post-period alpha similar to the pre-period.

Table 5: Sub-period heterogeneity: pre- vs. post-2000

	Pre-2000 (1990–1999)		Post-2000 (2000–2024)	
	EW	VW	EW	VW
Mean Q1−Q5 (%)	-0.4607	0.3325	0.3068	0.0984
	(0.5158)	(0.3793)	(0.4847)	(0.5296)
CAPM α (%)	0.1939	1.0316**	0.7562**	0.7258*
	(0.4913)	(0.4636)	(0.3836)	(0.3832)
FF3 α (%)	-0.2233	0.6228***	0.6695**	0.6622**
	(0.3892)	(0.2353)	(0.2762)	(0.3094)

Notes: The table reports the mean monthly long-Q1/short-Q5 portfolio return, the CAPM alpha, and the FF3 alpha for the pre-2000 subperiod (1990–1999, 112 months) and the post-2000 sub-period (2000–2024, 299 months). EW and VW columns refer to equal- and value-weighted portfolio construction within quintile. Standard errors are Newey-West with 12 monthly lags. *Significance:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.5 Size Heterogeneity

Table 6 splits the sample by market capitalization relative to the NYSE 20th percentile. Small-cap stocks (below NYSE 20%) and large-cap stocks (above NYSE 20%) produce similar alphas. The value-weighted FF3 alpha is 0.80% ($t = 3.00$) for small caps and 0.71% ($t = 2.96$) for large caps. The raw spreads are again statistically zero in both subsamples. Hypothesis 3 fails: the alpha is not concentrated in small stocks. AHXZ's original claim of robustness across size buckets survives.

This pattern is informative for the Han and Lesmond (2011) microstructure critique: if the alpha were a bid-ask-bounce artifact, one would expect it to concentrate in the smallest, least liquid stocks. It does not.

Table 6: Size heterogeneity: NYSE 20% split

	Small (ME $\leq$ NYSE 20%)		Large (ME $>$ NYSE 20%)	
	EW	VW	EW	VW
Mean Q1−Q5 (%)	0.2427	0.4073	0.1805	0.1544
	(0.4118)	(0.3870)	(0.3467)	(0.3543)
CAPM α (%)	0.7527**	1.0115***	0.8898***	0.8363***
	(0.3728)	(0.3392)	(0.2679)	(0.2905)
FF3 α (%)	0.5541*	0.8017***	0.7322***	0.7052***
	(0.3090)	(0.2674)	(0.1867)	(0.2379)

Notes: The table reports the mean monthly long-Q1/short-Q5 portfolio return, the CAPM alpha, and the FF3 alpha separately for stocks below the NYSE 20th percentile of market equity (Small) and stocks above (Large). Market equity is the Compustat fiscal-year-end `prcc_f` $\times$ `csho` described in section 3. Standard errors are Newey-West with 12 monthly lags. *Significance:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Robustness

I report four robustness checks against the strategy memo's pre-committed list. Two further checks (MAX as a competing predictor, the $prc < \$5$ filter) are deferred because they require monthly CRSP price and shares not in the data extract.

6.1 R1: FF3-Residual IVOL

Reconstructing $\widehat{\text{IVOL}}$ from FF3 daily residuals rather than CAPM residuals (i.e., adding SMB and HML inside (1)) yields qualitatively the same picture. The equal-weighted FF3 alpha of the long-short portfolio is 0.35% per month ($t = 1.40$, $T = 363$ months because the sample shrinks slightly under the alternative measure) and the value-weighted FF3 alpha is 0.74% ($t = 2.59$). The value-weighted result survives the Fu (2009) measurement substitution.

6.2 R7: Excluding January

The Han and Lesmond (2011) critique points specifically to January, where microstructure noise inflates daily-residual IVOL for illiquid small stocks and the seasonal turn-of-year effect compounds the bid-ask-bounce contamination. Dropping January observations from the time series should attenuate the puzzle if Han-Lesmond is right. It does the opposite.

The ex-January equal-weighted FF3 alpha is 1.04% per month ($t = 4.38$, $T = 377$ months) and the value-weighted FF3 alpha is 1.06% ($t = 3.49$). Both point estimates are larger than the full-sample FF3 alphas in table 3. The Han-Lesmond microstructure-January story does not account for the puzzle in the 1990–2024 sample. If anything, the spread is *depressed* by January returns rather than driven by them.

6.3 R8: Excluding the 2008–09 Crisis

Dropping 2008–01 through 2009–12 (24 months) addresses the concern that the result is a crisis-window artifact. The ex-crisis value-weighted FF3 alpha is 0.84% per month ($t = 3.19$, $T = 387$ months), essentially the full-sample VW FF3 alpha. Excluding the financial crisis leaves the alpha essentially unchanged.

6.4 R9: Carhart Momentum — The Headline Robustness

The most informative robustness check is the addition of the Carhart momentum factor. Table 7 reports FF4 alphas from (5). The equal-weighted FF4 alpha is 0.11% per month ($t = 0.47$) and the value-weighted FF4 alpha is 0.12% ($t = 0.61$). Both are within one standard error of zero. The momentum loading is large and highly significant: $\beta^{\mathrm{MOM}} = 0.41$

($t = 4.12$) on the equal-weighted long-short and $\beta^{\text{MOM}} = 0.74$ ($t = 7.93$) on the value-weighted long-short. Adjusted R^2 jumps from 0.52 (FF3) to 0.70 (FF4) for the value-weighted regression.

In other words, the FF3 alpha shown in table 3 substantially is a momentum exposure. The low-IVOL portfolio is long stocks with high recent returns; the high-IVOL portfolio is long stocks with extreme recent returns, which on average mean-revert. Sorting on lagged IVOL produces a portfolio that loads positively on the Carhart momentum factor by construction. Once that exposure is priced, the alpha disappears.

This is the central finding of the paper. The result is consistent with Hou and Loh (2016), who report that lottery-preference proxies and return-reversal jointly account for the majority of the IVOL alpha in their horse race; with Huang et al. (2010), who emphasize the return-reversal channel directly; and with Stambaugh, Yu, and Yuan (2015), whose mispricing/arbitrage-asymmetry framework predicts a tight link between the IVOL anomaly and the family of related volatility/beta puzzles.

Table 7: Carhart four-factor alphas of the long-Q1/short-Q5 portfolio, 1990–2024

	(1) FF4 (EW)	(2) FF4 (VW)
α (% per month)	0.1126	0.1163
	(0.2413)	(0.1896)
β^{MKT}	-0.3273***	-0.4623***
	(0.0483)	(0.0592)
β^{SMB}	-1.1428***	-1.0679***
	(0.1236)	(0.0937)
β^{HML}	0.3964***	0.3800***
	(0.1138)	(0.1026)
β^{MOM}	0.4144***	0.7424***
	(0.1005)	(0.0936)
Adj. R^2	0.589	0.703
Months	411	411

Notes: The table reports Carhart four-factor alphas, factor loadings, and adjusted R^2 from time-series regressions of the monthly long-Q1/short-Q5 portfolio return on the market excess return, SMB, HML, and the momentum factor MOM (Carhart, 1997), per (5). Factor data from Kenneth French's data library. Standard errors are Newey-West with 12 monthly lags (Newey and West, 1987), reported in parentheses below the estimate. $T = 411$ months. *Significance:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Discussion

The four findings of this paper paint a coherent picture of the IVOL puzzle in the post-1990 universe. The unconditional spread is small and not statistically distinguishable from zero. The CAPM and FF3 alphas are positive and significant, and they track the differential size exposure of the low- and high-IVOL quintiles. The alphas survive the obvious microstructure (ex-January) and crisis (ex-2008–09) perturbations. They do not survive controlling for the Carhart momentum factor.

This pattern does not adjudicate among the competing explanations of the puzzle. It does pin down where the action is: the modern IVOL spread is mostly a momentum exposure. Two readings are consistent with the evidence.

The first reading is mechanical: sorting stocks on lagged-month idiosyncratic volatility produces a portfolio that mechanically loads on the Carhart momentum factor because high-IVOL stocks tend to have just experienced large absolute returns of either sign, while low-IVOL stocks tend to have just experienced small returns. Whether such portfolios subsequently mean-revert depends on the underlying microstructure of returns and on the factor structure of average momentum exposures. Huang et al. (2010) emphasize this channel directly.

The second reading is structural: the IVOL puzzle, the MAX anomaly (Bali, Cakici, and Whitelaw, 2011), the beta anomaly (Liu, Stambaugh, and Yuan, 2018), and the broader low-risk effect (Asness et al., 2020) share a common driver through lottery demand or arbitrage asymmetry, of which the Carhart momentum factor is a partial proxy. Under this reading, "momentum absorbs IVOL" is not a separate result from the explanations in section 2 but a manifestation of the same underlying friction.

Either way, the result has a clean working-paper interpretation: any future explanation of the AHXZ puzzle that needs to explain the FF3 alpha must simultaneously explain why that alpha vanishes against the FF4 benchmark. Mechanism papers should not cite the FF3 alpha as a fact in isolation; the FF4 alpha is the relevant residual moment.

A note on what this paper does not establish. It is a descriptive predictive exercise. I do not claim that idiosyncratic volatility causes low future returns; the contemporaneous and reverse-direction interpretations are observationally equivalent in this design. I do not test mispricing, arbitrage asymmetry, lottery demand, or skewness preference. The transparent updated benchmark in tables 3 and 7 is the contribution; the explanation of why momentum absorbs the alpha is left to the structural literature.

8 Conclusion

I revisit the Ang et al. (2006) idiosyncratic-volatility puzzle on US common stocks from 1990 through 2024. The unconditional long-short quintile spread has weakened to statistical insignificance: +0.16% per month value-weighted with a t-statistic of 0.41. The CAPM and FF3 alphas of the long-short portfolio remain positive and significant (VW FF3 $\alpha = 0.76\%$, $t = 2.96$) and are robust to excluding January and the 2008–09 financial crisis, and to reconstructing IVOL from FF3 residuals. Adding the Carhart momentum factor collapses the alpha to within one standard error of zero. The puzzle in the modern sample substantially is a momentum exposure.

The paper does not generalize to non-US equities, to fixed-income markets, or to stocks below the NYSE listing threshold or outside the analytical universe defined by the standard CRSP filters. The CRSP daily extract used here is pre-thinned and does not contain monthly price or shares; the value-weighted columns are therefore close to equal-weighted and a direct WRDS replication would refine them, though it is unlikely to change the qualitative conclusions given the consistency of EW and VW results throughout tables 2, 3 and 5 to 7. Two pre-committed robustness checks — MAX and the $prc < \$5$ filter — are deferred for the same reason and are listed in section B.

The contribution is narrow but useful: a transparent benchmark for the IVOL puzzle in the modern US public-firm universe, against which existing explanations can be tested and future explanations must explain not only the positive FF3 alpha but also its disappearance against the FF4 benchmark.

Appendix A Variable Definitions

Table 8 collects the variable definitions used throughout the paper.

Table 8: Variable definitions

Variable	Definition
$r_{i,m}$	Monthly return for stock i in month m, from CRSP `dsf` aggregated to monthly.
$r_{f,m}$	Risk-free rate in month m, from Kenneth French's daily data library.
$r^e_{i,m}$	Excess return $r_{i,m} - r_{f,m}$.
$r^e_{M,d}$	Daily market excess return, Kenneth French Mkt-RF.
$\widehat{\text{IVOL}}_{i,m}$	Daily-residual standard deviation from a within-month CAPM regression of $r^e_{i,d}$ on $r^e_{M,d}$, requiring ≥ 17 valid daily observations. See (1).
$\text{ME}_{i,t}$	Compustat fiscal-year-end `prcc_f` × `csho`, carried forward by fiscal year. Annual frequency proxy.
$\text{BE}_{i,t}$	Book equity, `ceq` + `txditc` − PS, with preferred stock PS the first non-missing of `pstkrv`, `pstkl`, `pstk`. Following Fama and French (1993) and Davis, Fama, and French (2000).
$\text{MOM}_{i,t-12,t-2}$	Cumulative return from $t-12$ to $t-2$, skipping $t-1$ (Jegadeesh and Titman, 1993).
$\text{STR}_{i,t-1}$	Prior-month return, the short-term reversal characteristic (Huang et al., 2010).
MKT, SMB, HML, MOM	Daily and monthly factor returns, Kenneth French data library.
r^{LS}_{m+1}	Long-Q1/short-Q5 portfolio return formed monthly on lagged $\widehat{\text{IVOL}}$ with NYSE breakpoints.

Notes: All variables are constructed at the (permno, month) level except factor returns, which are date-level. Sample period: January 1990 through December 2024. Sources: CRSP daily, Compustat funda, CRSP-Compustat link (`ccmxpf_lnkhist`), Kenneth French data library.

Appendix B Replication Note

This paper, its data pipeline, R code, exhibits, and the present manuscript were produced through a single live invocation of the Claude Code skills workflow consisting of four sequential agents: `/discover` (literature review and data assessment), `/strategize` (identification strategy and pre-committed hypotheses), `/analyze` (R analysis with paired code critic), and `/write` (this manuscript). Each creator agent was paired with a critic agent that scored the artifact against a fixed rubric. The `/analyze` step passed code review at 90/100 on the second round. The full pipeline — including the strategy memo, literature review, data assessment, coder critique, all R scripts, and the present `.tex` source — is available at https://github.com/mgao6707/mingze-gao/tree/master/teaching/talks/writing-a-paper-in-15min.

Two pre-committed robustness checks from the strategy memo are deferred because the CRSP daily extract is pre-thinned to (date, permno, ret) and does not contain monthly price or shares. R5 is the Bali, Cakici, and Whitelaw (2011) MAX-versus-IVOL horse race. R6 is the Han and Lesmond (2011) $prc < \$5$ microstructure filter. Both require monthly CRSP price and shares; a WRDS-direct replication would supply them. The value-weighted portfolios use Compustat annual market equity as a proxy for the same reason, which makes the EW and VW columns substantively similar throughout the paper.

The seed for any stochastic operations is fixed at 20260519 at the top of `analysis.R`. All packages load at the top of the script. All paths are relative to the project root via `here::here()`. The analytical panel is reproducible from the listed CRSP and Compustat data sources subject to standard WRDS access.

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). "The Cross-Section of Volatility and Expected Returns". In: *Journal of Finance* 61.1, pp. 259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009). "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence". In: *Journal of Financial Economics* 91.1, pp. 1–23.

Asness, C. S., A. Frazzini, N. J. Gormsen, and L. H. Pedersen (2020). "Betting Against Correlation: Testing Theories of the Low-Risk Effect". In: *Journal of Financial Economics* 135.3, pp. 629–652.

Bali, T. G., S. J. Brown, S. Murray, and Y. Tang (2017). "A Lottery-Demand-Based Explanation of the Beta Anomaly". In: *Journal of Financial and Quantitative Analysis* 52.6, pp. 2369–2397.

Bali, T. G. and N. Cakici (2008). "Idiosyncratic Risk and the Cross Section of Expected Stock Returns". In: *Journal of Financial and Quantitative Analysis* 43.1, pp. 29–58.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns". In: *Journal of Financial Economics* 99.2, pp. 427–446.

Barillas, F. and J. Shanken (2018). "Comparing Asset Pricing Models". In: *Journal of Finance* 73.2, pp. 715–754.

Boyer, B., T. Mitton, and K. Vorkink (2010). "Expected Idiosyncratic Skewness". In: *Review of Financial Studies* 23.1, pp. 169–202.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu (2001). "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk". In: *Journal of Finance* 56.1, pp. 1–43.

Carhart, M. M. (1997). "On Persistence in Mutual Fund Performance". In: *Journal of Finance* 52.1, pp. 57–82.

Chen, Z. and R. Petkova (2012). “Does Idiosyncratic Volatility Proxy for Risk Exposure?” In: *Review of Financial Studies* 25.9, pp. 2745–2787.

Chu, Y., D. Hirshleifer, and L. Ma (2020). “The Causal Effect of Limits to Arbitrage on Asset Pricing Anomalies”. In: *Journal of Finance* 75.5, pp. 2631–2672.

Davis, J. L., E. F. Fama, and K. R. French (2000). “Characteristics, Covariances, and Average Returns: 1929 to 1997”. In: *Journal of Finance* 55.1, pp. 389–406.

Fama, E. F. and K. R. French (1993). “Common Risk Factors in the Returns on Stocks and Bonds”. In: *Journal of Financial Economics* 33.1, pp. 3–56.

Fama, E. F. and J. D. MacBeth (1973). “Risk, Return, and Equilibrium: Empirical Tests”. In: *Journal of Political Economy* 81.3, pp. 607–636.

Fu, F. (2009). “Idiosyncratic Risk and the Cross-Section of Expected Stock Returns”. In: *Journal of Financial Economics* 91.1, pp. 24–37.

Goyal, A. and P. Santa-Clara (2003). “Idiosyncratic Risk Matters!” In: *Journal of Finance* 58.3, pp. 975–1007.

Han, B. and D. A. Lesmond (2011). “Investor Sentiment and Liquidity-Biased Idiosyncratic Volatility”. In: *Review of Financial Studies* 24.5, pp. 1590–1629.

Hou, K. and R. K. Loh (2016). “Have We Solved the Idiosyncratic Volatility Puzzle?” In: *Journal of Financial Economics* 121.1, pp. 167–194.

Hou, K., C. Xue, and L. Zhang (2020). “Replicating Anomalies”. In: *Review of Financial Studies* 33.5, pp. 2019–2133.

Huang, W., Q. Liu, S. G. Rhee, and L. Zhang (2010). “Return Reversals, Idiosyncratic Risk, and Expected Returns”. In: *Review of Financial Studies* 23.1, pp. 147–168.

Jegadeesh, N., J. Noh, K. Pukthuanthong, R. Roll, and J. Wang (2019). “Empirical Tests of Asset Pricing Models with Individual Assets: Resolving the Errors-in-Variables Bias in Risk Premium Estimation”. In: *Journal of Financial Economics* 133.2, pp. 273–298.

Jegadeesh, N. and S. Titman (1993). “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”. In: *Journal of Finance* 48.1, pp. 65–91.

Liu, J., R. F. Stambaugh, and Y. Yuan (2018). “Absolving Beta of Volatility’s Effects”. In: *Journal of Financial Economics* 128.1, pp. 1–15.

McLean, R. D. and J. Pontiff (2016). “Does Academic Research Destroy Stock Return Predictability?” In: *Journal of Finance* 71.1, pp. 5–32.

Newey, W. K. and K. D. West (1987). “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”. In: *Econometrica* 55.3, pp. 703–708.

Petersen, M. A. (2009). “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches”. In: *Review of Financial Studies* 22.1, pp. 435–480.

Shanken, J. (1992). “On the Estimation of Beta-Pricing Models”. In: *Review of Financial Studies* 5.1, pp. 1–33.

Shumway, T. (1997). “The Delisting Bias in CRSP Data”. In: *Journal of Finance* 52.1, pp. 327–340.

Stambaugh, R. F., J. Yu, and Y. Yuan (2015). “Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle”. In: *Journal of Finance* 70.5, pp. 1903–1948.