Refreshing Factors

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Fama and French (1993): Original Timing Convention

"To ensure that the accounting variables are known before the returns they are used to explain, we match the accounting data for all fiscal yearends in calendar year $t-1$ (1962–1989) with the returns for July of year t to June of $t+1$. The 6-month (minimum) gap between fiscal yearend and the return tests is conservative."

Fama, Eugene F., and Kenneth R. French (1993), *Journal of Financial Economics*.

The Fama-French Factors on May 1, 2023

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Signal	Mismatch
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OP	26.3
INV	50.4
Average	**31.0**

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May 2023 monthly factor returns

Factor	Stale (%)	Fresh (%)	Diff
SMB	0.56	-0.54	-1.11
HML	-8.03	-5.74	2.28
RMW	-2.92	-4.12	-1.20
CMA	-6.93	-0.16	6.77

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This paper starts from a simple idea:

Canonical Fama-French factors are current returns on stale proxy portfolios; once you freshen the portfolios, things will change.

We focus on the implementation/timing gap

Gap 1: Proxy construction gap

Latent factors are not observed; we proxy them with traded portfolios.

Gap 2: Implementation/Timing gap

Current returns are from portfolios formed using stale information.

This paper's focus

We focus on the timing gap and ask whether fresher timing (i) changes the factor returns and (ii) improves the pricing of assets.

Objects Used Throughout The Talk

$$S_t \equiv r_t^{\text{stale}} \qquad F_t \equiv r_t^{\text{fresh}} \qquad \Delta_t \equiv F_t - S_t$$

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Gap 1: Proxy construction gap

Are fresh factors different? Yes.

Do fresh factors improve pricing? No.

$S_t = r_t \qquad F_t = r_t \qquad \Delta_t = F_t - S_t$

We focus on the implementation/timing gap

Gap 1: Proxy construction gap

Are fresh factors different? Yes.

Do fresh factors improve pricing? No.

Does the Δ improve pricing? Yes.

Why?

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Why?

By allowing asset returns to load differently on the slow-moving and innovation/update part of factors.

Related Work: Timing, construction, and testing logic

- **Asness and Frazzini (2013):** similar motivation that stale sorting inputs can materially change factor returns. Focus only on HML (fast-value-premium).
- **Akey, Robertson, and Simutin (2026):** similar view that traded factor portfolios are noisy proxies for latent risks.
- **Shanken (1987); Barillas and Shanken (2017, 2018):** provides the model-comparison logic we use, including comparisons across non-nested models.

This paper's contribution

We rebuild the FF factors using fresher information, but fresh factors by themselves help pricing only a little. Bigger gains come from separating factors into stale and update parts. Our mechanism tests suggest this works because it gives a better way to price assets, not just a better filtered factor.

Roadmap

1. Replicate the FF benchmark using standard timing conventions.
   - Our replication is credible, but these factors are stale!
2. Adjust only the timing to construct Fresh factors.
   - Fresh factors are materially different, especially HML and CMA.
3. Test whether Fresh improves pricing relative to Stale.
   - Gains are present but small and selective.
4. Test pricing with Stale $+\Delta$ ($\Delta \equiv F - S$).
   - Pricing gains are much larger.
5. Explain why by developing two mechanisms.
   - Evidence favors the best-pricing-basis interpretation (not a better filtered factor).

Credible stale benchmark and the main fresh proxy

Two Main Objects

- **Stale benchmark:** annual-style implementation aligned with canonical FF timing.
- **Fresh factors:** same basic architecture using monthly, point-in-time sorting information.

Replication quality (1995–2024)

- Avg correlation vs Official FF5: **0.9886**.
- Avg variance retained: **97.65%**.

Key Points

We've replicated the official factors very closely. Our fresh factors code is simple adjustments to the replication: at the end of every month, reform portfolios based on updated financial and market information.

Stale $\neq$ Fresh, especially in HML and CMA

Fresh vs Stale, 1995–2024 monthly

Factor	Corr	MeanDiff (bp)	VarRetained (%)
SMB	0.962	1.9	92.5
HML	0.811	-1.1	49.0
RMW	0.946	4.4	87.0
CMA	0.876	15.3**	71.2

- All four factor objects move when timing is refreshed.
- Correlations are much lower for HML and CMA.
- **Note:** MeanDiff $\approx \Delta \equiv F - S$ from earlier.

Takeaway

Fresh timing materially changes factor objects; the main action is in HML and CMA.

Δ material after FF5 + MOM + STREV controls

$\Delta \equiv F - S$ (monthly, 1995–2024)

Factor	Alpha (bp/mo)	t-stat
SMB	3.7	0.94
HML	20.6***	2.85
RMW	6.9	1.20
CMA	27.5***	3.38

$$\Delta_t^k = \alpha_k + b_k' FF5_t^S + c_k\, MOM_t + d_k\, STREV_t + \varepsilon_t^k$$

Dynamic factors help explain for Δ_{HML} ($R^2 \approx 0.72$), α remains large (20.6 bp/mo); for Δ_{CMA} it also remains large (27.5 bp/mo).

Takeaway

The update return (Δ) is not just relabeled momentum/reversal; the strongest residual pricing content is in HML and CMA.

Does fresh-only replacement improve pricing?

Horse-race tests (cross-sectional fit)

- Compare **Fresh** against **Stale**.
- Include $MOM + STREV$ in all pricing models.
- Test assets: 49 Industries, 212 OpenAP, 13 JKP.
- Broad test: stock-level panel.

$$\Delta CS\,R^2 = CS\,R^2_F - CS\,R^2_S$$

$$\Delta RMSE = RMSE_S - RMSE_F$$

Barillas-Shanken Tests

- **Reverse spanning:** can S span F, and can F span S?
- **Bias-adjusted θ^2:** does fresh give a better overall risk-return menu than stale?
- Higher $\hat{\theta}^2_{\text{adj}}$ means better risk-adjusted signal-to-noise ratio.

$$\theta^2 = \mu_f' \Sigma_f^{-1} \mu_f$$

$$\text{Wins} = \sum_i \mathbf{1}(|\hat{\alpha}_{i,F}| < |\hat{\alpha}_{i,S}|)\,,\ \text{reported as Wins}/N$$

$$\text{SigAlpha}(Sm) = \sum_i \mathbf{1}(|t(\hat{\alpha}_{i,Sm})| \geq 1.96)\,,\ Sm \in \{S, F\}$$

Fresh-only replacement helps selectively

Model-fit diagnostics

Asset set	CS R^2_S (%)	ΔCS R^2	RMSE$_S$ (bp)	ΔRMSE
49 Industries	36.6	0.33 (1.93)	361.7	1.12 (2.16)
212 OpenAP Anoms	46.1	0.42 (2.70)	266.1	1.40 (1.90)
13 JKP Anoms	93.1	0.23 (2.20)	36.3	0.97 (2.90)
CRSP Stocks	14.3	-0.20 (-1.96)	964.4	-0.79 (-0.63)

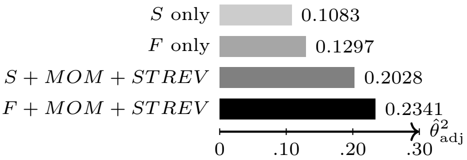
Alpha diagnostics

Asset set	Fresh wins	Sig α count (S/F)
49 Industries	24/49	5/4
212 OpenAP Anoms	93/212	89/91
13 JKP Anoms	8/13	2/3
CRSP Stocks	2344/4792	374/377

Fresh doesn't dominate Stale.

Barillas-Shanken checks: fresh vs stale

Bias-adjusted $\hat{\theta}^2$ (visual)



The gaps from S to F are both non-significant in pairwise tests.

Reverse spanning

Direction	p-value	Read
$F \mid S$	0.0192	reject
$S \mid F$	0.2853	no reject

Fresh adds some span beyond stale, but stale is not rejected against fresh.

Fresh still doesn’t dominate Stale.

Fresh is directionally better, but overall, the stale-versus-fresh difference is not decisive.

Stale + Δ beats Fresh replacement

Same baseline model, same controls, same test assets.
Only the HML/CMA representation changes.

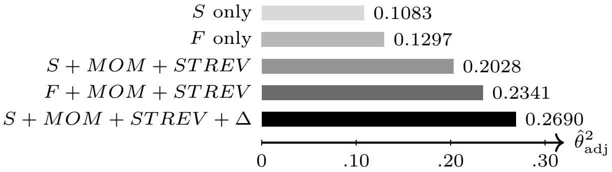
	Fresh replacement		Stale + Δ	
Asset set	ΔCS R^2	ΔRMSE	ΔCS R^2	ΔRMSE
49 Industries	0.33 (1.93)	1.12 (2.16)	**6.55 (21.07)**	**20.33 (15.26)**
212 OpenAP Anoms	0.42 (2.70)	1.40 (1.90)	**5.83 (13.38)**	**18.37 (6.48)**
13 JKP Anoms	0.23 (2.20)	0.97 (2.90)	**3.77 (14.00)**	**13.41 (12.47)**
CRSP Stocks	-0.20 (-1.96)	-0.79 (-0.63)	**1.67 (8.65)**	**13.52 (5.26)**

Main takeaway

Fresh-only helps a little and can even hurt. Adding Δ to Stale produces large gains in every setting, including stocks.

Barillas-Shanken checks with Δ added

Bias-adjusted squared Sharpe ($\hat{\theta}^2$)



Reverse spanning

Direction	p-value(s)	Read
$F \mid S$	0.0192	reject
$S \mid F$	0.2853	no reject
$S{+}\Delta \mid S$	0.0009	reject

Overall, Stale $+\Delta$ is better than Fresh replacement.

If Stale + Δ beats Fresh, what is going on?

$$F_t = S_t + \Delta_t \qquad \Delta_t \equiv F_t - S_t$$

What we just showed

- Fresh-only replacement improves pricing modestly and selectively.
- Stale + update (Δ) produces much larger gains.

Question: Why does adding Δ help so much?

- Is Δ mostly just correcting noise in the factor proxy?
- Or does pricing want separate exposures to stale anchor and update return?

Mechanism 1: can one filtered factor explain the gains?

Start with objects

$$f_t^* \equiv \text{ideal current factor payoff (latent, unobserved)}$$

$$\nu_t \equiv f_t^* - S_t \quad \text{(true missing update relative to stale)}$$

$$\Delta_t \equiv F_t - S_t \quad \text{(observed update from refreshing)}$$

Core signal-extraction question

How informative is observed Δ_t about the true missing update ν_t?

One-factor filtered family

$$F_t^\kappa = S_t + \kappa\Delta_t = (1-\kappa)S_t + \kappa F_t$$

Key Point

F is the least stale observable one-factor proxy, but that does not automatically make it the best one-factor proxy for the ideal factor f_t^*.

Mechanism 1 implies a testable κ^*

One-factor filtered family

$$F_t^{\kappa} = S_t + \kappa\Delta_t = (1-\kappa)S_t + \kappa F_t$$

Interpretation of κ

- $\kappa = 1$: raw Fresh is about right as a one-factor proxy.
- $0 < \kappa < 1$: Fresh moves in the right direction but too much.
- $\kappa > 1$: Fresh moves in the right direction but not far enough.
- $\kappa \approx 0$: Δ carries little useful one-factor signal.

What must hold for this channel

- Stale still has signal.
- Δ has incremental signal.
- Δ is an imperfect measurement of the ideal update (ν).

Mechanism 2: separate stale and update exposures

Pricing-basis channel

$$R_{i,t} = \alpha_i + \Gamma_i' X_t + b_i^S S_t + b_i^\Delta \Delta_t + \varepsilon_{i,t+1}$$

Economic intuition

- S_t is the slow-moving stale anchor.
- Δ_t is the revision margin from refreshing assignments.
- Different assets can load differently on anchor versus revision.

What this implies

- One common collapse $b_i(S + \kappa\Delta)$ can be too restrictive.
- The pair (S, Δ) can be a better traded pricing basis even without a new primitive factor.

Testable implication

If this channel dominates, $b_i^S S + b_i^\Delta \Delta$ should keep residual gains over $b_i(S + \kappa\Delta)$.

Three ways to price the stale/update dimension

B0: Fresh-only $R_{i,t} = \alpha_i + \Gamma_i' X_t + b_i F_t + \varepsilon_{i,t+1}$

B1: Filtered one-factor $R_{i,t} = \alpha_i + \Gamma_i' X_t + b_i (S_t + \kappa \Delta_t) + \varepsilon_{i,t+1}$

B2: Stale + Update $R_{i,t} = \alpha_i + \Gamma_i' X_t + b_i^S S_t + b_i^\Delta \Delta_t + \varepsilon_{i,t+1}$

Restrictions

- **B0** sets $\kappa = 1$ and forces $b_i^S = b_i^\Delta$.
- **B1** allows $\kappa \neq 1$, but one common κ must work for every asset.
- **B2** lets stale and update enter separately.

Main question

Does moving from **B1** to **B2** materially reduce pricing errors?

Main mechanism test: can the best filtered factor capture the gains?

If the one-factor story is right, **B1** should capture most of the gains, so the extra step from **B1** to **B2** should be small.

	B0 → B1		**B1 → B2**	
Metric	Avg improvement	% improved	Avg improvement	% improved
ΔCS R^2 (pct-pt)	0.12	58.3%	**2.08**	**100.0%**
ΔCS RMSE (bp)	0.73	83.3%	**6.76**	**100.0%**

"Improved" means the later model beats the earlier one in that context.

Takeaway

The best one-factor collapse helps only modestly. The large gains remain only when stale and update are allowed to price separately.

Supporting evidence: no clean common κ

Bottom line

B1 improves modestly, but **B2** remains much stronger in both R^2 and RMSE.

Other tests line up with the same conclusion

- Equal-loading restrictions between stale and update often fail.
- Common-κ fit is uneven across asset sets.
- The estimated κ does not transfer cleanly across settings.

How to read this: better pricing basis, not a new factor

$$F_t = S_t + \Delta_t$$

What we are saying

- S_t: the **stale anchor** — the broad, slow-moving factor spread.
- Δ_t: the **update return** — the payoff to refreshing stale assignments and weights.
- Different assets can want different mixes of these two pieces.

What we are not saying

- Δ is not the true latent factor.
- Δ is not automatically a new primitive factor.
- Fresh factors still matter; they help reveal the update.

What different loadings mean

An **anchor-heavy** asset covaries mostly with the broad stale spread. An **update-heavy** asset covaries mainly with the return to refreshing stale assignments. That is why (S, Δ) can price better than F alone.

One thing to remember: Fresh is not enough

Three-part summary

- Canonical FF factors are current returns on stale proxy portfolios.
- Refreshing changes the factor objects, especially HML and CMA.
- The big gains come from separating the stale anchor from the update return.

Main message

This is not a new-factor story. It is a better traded representation of the same factor dimension: fresh matters, but fresh alone is not enough.