

The Duration Gap: Value-at-Risk, Interest-Rate Swaps and the 2026 Losses of Chile's Most Conservative Pension Fund

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Abstract

Between January and September 2026, Fund E, the most conservative of Chile's five mandatory pension fund types, lost about ten per cent in real terms, its second-worst result on record, while the funds' positions in foreign interest-rate derivatives swung to a reported valuation loss of about US\$7.7 billion. This article asks why standard Value-at-Risk (VaR) measures did not warn of the loss. Using daily unit values for the seven pension fund administrators (AFPs) from January 2015 to October 2026, Chilean and US government yields and the exchange rate, I estimate the funds' effective duration to US long-term yields and backtest six VaR models at daily and monthly horizons. Four hypotheses were stated before estimation. First, Fund E's sensitivity to the US ten-year yield rose from about 0.2 years in 2016–2019 to 7.2 years in 2026 (change 6.3 years, $z = 11.4$), rising from late 2022 and accelerating from late 2023, consistent with the build-up of receive-fixed dollar swaps; US rates account for – 7.9 of the – 6.5 percentage points of nominal return in January–September 2026. Second, contrary to the hypothesis, daily 99% VaR models broadly met their coverage in 2026 (three to six exceptions against about two expected); the loss was a persistent drift, not a sequence of tail days. Third, an exposure-adjusted VaR, which applies the current factor exposure to a long history of rate moves, rose to 7.4% of the fund for a one-month horizon in June 2026, more than twice the 3.5% given by historical simulation scaled by the square root of time, which was then at its lowest level since early 2024; only the exposure-adjusted measure covered the September 2026 loss of 5.1%, in all seven AFPs and in nine window combinations. Fourth, differences in pre-shock exposure across AFPs did not significantly predict the size of the loss (Spearman $\rho = 0.50$, exact $p = 0.13$). The gap between what a volatility-based VaR measures and what the portfolio is exposed to supports the stress-based derivatives limit that the regulator introduced in April 2026.

JEL classification: G23; G28; G32; G17; E43

1. Introduction

Chile's defined-contribution system lets members choose among five fund types, from Fund A, mostly equities, to Fund E, invested in fixed income and offered as the option for members close to retirement. In 2026 the conservative end of the system produced the largest losses. The Superintendencia de Pensiones reported a real return of – 10.39% for Fund E between January and September and – 4.92% in September alone (Emol, 2026). A Bloomberg report, based on the regulator's data, put the funds' mark-to-market position in foreign interest-rate derivatives at a loss of about US\$7.7 billion, compared with a gain of about US\$1.4 billion a year earlier (Bloomberg Línea, 2026). According to the Central Bank of Chile, as reported by the financial press, the funds' receive-fixed position in US-dollar interest-rate swaps grew from almost nothing in August 2023 to more than US\$230 billion of notional at the start of 2026, and derivatives had supplied close to half of the funds' duration (Diario Financiero, 2026).

A receive-fixed swap gains when rates fall and loses when they rise. Its economic effect resembles a leveraged holding of a long-term bond, financed at a floating rate, and it adds duration without using the fund's cash. When US long-term yields rose through 2026, from 4.1% at the end of 2025 to 5.3% at the end of September, the position lost value. In April 2026 the regulator had already introduced a limit on derivative exposure based on the estimated loss of the derivatives portfolio under stress scenarios, measured as a

share of the fund, together with a liquidity coverage requirement (Superintendencia de Pensiones, 2026). The limit takes effect in November 2026 (Bloomberg Línea, 2026).

This episode raises a question that is older than the swap position: what does Value-at-Risk measure when a portfolio changes its exposure faster than its own volatility history? VaR models estimate a quantile of the loss distribution from past returns. If exposure is built up during a calm period, the past returns describe a portfolio that no longer exists. The question matters for supervision because VaR limits have been proposed for pension funds as a risk-based alternative to quantitative limits (Berstein & Chumacero, n.d.), and because the regulator chose a stress-based measure instead.

The article makes three contributions. First, it measures, from public daily data alone, how the sensitivity of Chilean pension funds to US long-term yields changed between 2016 and 2026, controlling for local rates and the exchange rate. Second, it backtests six VaR models on the funds' realised returns at daily and monthly horizons, before and during the 2026 losses, for the system and for each of the seven AFPs. Third, it compares those models with an exposure-adjusted VaR that applies the current estimated exposure to a long history of factor moves, and documents when and by how much the two diverged. A bibliometric search in Scopus (Section 3) found no indexed study that backtests VaR against a realised loss of a defined-contribution pension system, or that studies interest-rate derivatives as a source of duration in Chilean pension funds.

The main results can be stated briefly. The funds' exposure to US rates rose sharply and significantly. Daily VaR did not fail in the formal sense: its exception rate in 2026 was close to nominal. The failure was one of horizon and composition. The one-month VaR obtained by scaling daily VaR with the square root of time was at its lowest level since early 2024 in May and June 2026, just before the July and September losses, while the exposure-adjusted measure was at its highest. Cross-sectional differences across AFPs point in the expected direction but are not significant with seven administrators.

2. Institutional background

Seven AFPs manage the mandatory accounts: Capital, Cuprum, Habitat, Modelo, PlanVital, ProVida and Uno, the last since 2019. Each runs the five fund types, and members may switch between types. Fund E is restricted to fixed-income instruments and, by default, receives the balances of members close to retirement, so its losses fall on people with little time to recover. On 30 September 2026 Fund E held about CLP 19.8 trillion across the seven AFPs, according to the regulator's daily data used in this study.

The investment regime allows the funds to use derivatives for hedging and for investment. Chilean pension funds have long been large participants in the local foreign-exchange forward market (Fernandez, 2006), and their flows affect the exchange rate and covered interest parity (Aldunate et al., 2025). Coordinated switching between fund types, encouraged by an advisory firm, also affected asset prices and pushed the funds towards more liquid securities (Da et al., 2018). The 2026 episode is different in kind: it concerns interest-rate swaps on foreign rates, used to add duration rather than to hedge currency risk.

The regulatory response predates the losses. The April 2026 rule replaced part of the earlier treatment with a limit on the estimated stress loss of the derivatives portfolio, expressed as a percentage of each fund, and a

coverage requirement for the liquidity needed to meet margin calls (Superintendencia de Pensiones, 2026). The design recalls the lesson of the 2022 gilt crisis in the United Kingdom, where pension funds using leveraged interest-rate hedges faced collateral calls when long-term yields rose quickly (Bank of England, 2022; Bonizzi et al., 2023).

3. Literature and hypotheses

3.1 Bibliometric search

I ran five Scopus queries on 14 October 2026 (TITLE-ABS-KEY, all years; full strings in the replication package). Pension funds combined with Value-at-Risk returned 44 records. Adding Chile, Chilean or Latin America returned none, which is consistent: none of the 44 records mentions Chile or Latin America. Pension funds combined with swaps or derivatives and with interest-rate risk, duration or leverage returned eight records, mostly tangential. Pension funds and derivatives in Chile returned two, both descriptive and published in 2003–2006. Pension funds combined with liability-driven investment, the gilt crisis or collateral calls returned three.

The 44 VaR records are dominated by portfolio optimisation under VaR or CVaR constraints and by asset–liability management for defined-benefit plans. Few evaluate whether a VaR measure anticipated a realised loss. The closest are a rolling-horizon backtest of Solvency II VaR models (Loois, 2015), an analysis of short-horizon risk regulation for long-term investors (Shi & Werker, 2012) and a study of how regulation shaped the investments of Brazilian pension funds (Cardoso et al., 2024). The literature on interest-rate swaps as risk-transfer instruments (Baker et al., 2021) and on UK pension funds' liquidity after 2022 (Bonizzi et al., 2023) does not address defined-contribution systems or VaR backtesting.

3.2 What VaR can and cannot see

VaR is the loss that is exceeded with a given probability over a given horizon. It is not a coherent risk measure and says nothing about losses beyond the quantile (Artzner et al., 1999; Acerbi & Tasche, 2002). Backtests compare the frequency and clustering of exceptions with their nominal level (Kupiec, 1995; Christoffersen, 1998; Basel Committee on Banking Supervision, 1996). Different VaR models can agree in calm periods and diverge sharply in stress (Danielsson et al., 2016).

Two mechanisms can make a VaR model miss a loss that builds up over weeks. The first is the horizon. Scaling a one-day VaR by the square root of the horizon assumes independent, identically distributed returns; it can understate or overstate multi-period risk when returns are serially dependent or when the distribution is not normal (Danielsson & Zigrand, 2006). Positive serial correlation is common in portfolios of less liquid assets whose prices adjust slowly (Getmansky et al., 2004). The second is composition. A model estimated on the fund's own past returns describes the risk of the past portfolio. If exposure is added through derivatives during a calm period, the return history contains little information about the new exposure. Factor-based approaches address this by mapping the current portfolio onto risk factors and applying the history of the factors (J.P. Morgan/Reuters, 1996; Jorion, 2007).

3.3 Hypotheses

Four hypotheses were stated before estimation.

H1. Fund E's sensitivity to US long-term yields increased significantly from 2023 onwards, controlling for Chilean yields and the exchange rate.

H2. Standard VaR models calibrated on trailing windows under-covered the 2026 losses at the daily horizon: more exceptions than nominal, clustered in time, and more so than in a control period.

H3. An exposure-adjusted VaR, built from the current exposure and a long history of factor moves, signalled higher risk before the 2026 losses than the standard models.

H4. Across AFPs, a higher pre-shock exposure to US yields is associated with a larger 2026 loss of Fund E.

The behaviour of one-month VaR obtained by square-root-of-time scaling was examined after the daily results were known. It is reported as exploratory evidence, not as a test of a pre-stated hypothesis.

4. Data

Pension funds. Daily unit values and fund assets for Funds A to E of all AFPs, 1 January 2015 to 12 October 2026, from the Superintendencia de Pensiones. The file distinguishes confirmed from provisional values; the provisional block repeats confirmed days and only confirmed records are kept. The asset-weighted system return uses the previous day's assets as weights. Returns are measured in logarithms and in per cent, nominal and in real terms (net of the change in the Unidad de Fomento, UF).

Rates and exchange rate. Daily observed dollar and UF, and secondary-market yields on Chilean central-bank and Treasury bonds in pesos (2, 5 and 10 years) and in UF (2, 5, 10, 20 and 30 years), from the Central Bank of Chile's statistical database. US Treasury constant-maturity yields (2, 5, 10 and 30 years) from FRED, Federal Reserve Bank of St. Louis.

Calendar. The analysis uses Chilean business days, defined as days with an observed dollar: 2,931 days from 5 January 2015 to 9 October 2026, the last day with both US and Chilean yields. Secondary-market yields are missing on days without trades (the ten-year peso yield is observed on 93% of days and the ten-year UF yield on 89%); the last quote is carried forward for at most three business days. Daily changes in yields are measured in basis points.

Validation. Using these data, the asset-weighted system real return of Fund E is – 10.2% for January–September 2026 and – 4.9% for September, against the regulator's published – 10.39% and – 4.92%. By AFP, the January–September real loss ranges from 9.9% (Uno) to 10.9% (Modelo). Table 1 describes the Fund E system return.

Table 1
Fund E (system) daily real return, descriptive statistics (%)

Period	Days	Mean	SD	Min	Excess kurtosis	Worst month	AR(1)
2016 to Sep 2019	931	0.021	0.131	-1.08	13.65	-1.99	0.32
Oct 2019 to 2022	813	-0.007	0.507	-4.19	12.26	-4.45	0.35
2023 to 2025	743	0.009	0.423	-1.78	3.01	-5.75	0.20
2026 (to 9 Oct)	195	-0.049	0.356	-1.05	0.48	-5.05	0.16
Notes: Daily log returns in per cent, net of the change in the UF. Worst month is the lowest calendar-month sum of daily returns in the period. AR(1) is the first-order autocorrelation.							

Daily volatility in 2026 (0.36%) was lower than in 2019–2022 (0.51%) or 2023–2025 (0.42%), and the worst day of 2026 (-1.05%) was mild by the standards of the period. Two earlier months, October and December 2024, produced larger monthly losses (-5.75% and -5.47%) than September 2026 (-5.05%). What sets 2026 apart is the sequence of negative months: April, May, July and September.

5. Methods

5.1 Effective duration

The sensitivity of a fund's daily return r_t to rates is estimated with

$$r_t = \alpha + \beta_0 \Delta y_{US,t} + \beta_1 \Delta y_{US,t-1} + \gamma \Delta y_{CLP,t} + \delta \Delta y_{UF,t} + \theta \Delta s_t + \varepsilon_t \quad (1)$$

where Δy_{US} is the daily change in the US ten-year yield, Δy_{CLP} and Δy_{UF} are the changes in the Chilean ten-year peso and UF yields, and Δs is the percentage depreciation of the peso. The lagged US term allows for the time difference between the close of the US market and the valuation of foreign positions (Dimson, 1979). With returns in per cent and yield changes in basis points, the US effective duration in years is

$$D_{US} = -100 (\beta_0 + \beta_1) \quad (2)$$

and analogous expressions give the local durations. Eq. (1) is estimated by period with Newey–West standard errors (five lags; Newey & West, 1987), on rolling 126-day windows, and in a pooled model with period interactions to test whether D_{US} changed between 2016–2022 and 2025–2026. As a robustness check, the US ten-year yield is replaced by the thirty-year yield.

5.2 Value-at-Risk models

Six models produce one-day-ahead forecasts at 99% and 95%, each using only information up to the previous day: historical simulation on 250 days (HS-250); a normal model with 250-day mean and standard deviation; RiskMetrics exponential smoothing with $\lambda = 0.94$ (J.P. Morgan/Reuters, 1996),

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) r_{t-1}^2, \text{VaR}_t = -z_{1-\alpha} \sigma_t \quad (3)$$

a GARCH(1,1) model with Student-t innovations (Bollerslev, 1986, 1987), estimated on 1,000 days and re-estimated every 21 days with daily variance updating; filtered historical simulation on the GARCH standardised residuals (Barone-Adesi et al., 1999); and the exposure-adjusted model described next.

5.3 Exposure-adjusted VaR

On each day t , the coefficients $\tilde{\mathbf{b}}_t$ of Eq. (1) are estimated on the previous 126 days. The systematic part of the next-period return is simulated by applying $\tilde{\mathbf{b}}_t$ to the factor moves $\mathbf{F}_j$ observed over the previous $H = 1,000$ days, and the idiosyncratic part by the empirical quantile of the 126-day residuals. For a horizon of h days,

$$\text{VaR}_t^{\text{EXP},h} = \sqrt{[Q_\alpha(-\tilde{\mathbf{b}}_t' \mathbf{F}_j^{(h)})]^2 + h [Q_\alpha(-\hat{\varepsilon})]^2} \quad (4)$$

where $\mathbf{F}_j^{(h)}$ are overlapping h -day sums of factor changes and Q_α is the empirical α -quantile. For $h = 1$ the measure is the daily exposure-adjusted VaR; for $h = 21$ it is a one-month VaR that uses multi-day factor moves directly instead of scaling. The quadrature sum treats the two parts as independent, which is an approximation. The measure resembles a stress test calibrated on history: it asks what the current exposure would have lost under the rate moves of the last four years.

5.4 Backtests

A daily exception occurs when $r_t < -\text{VaR}_t$. Unconditional coverage is tested with Kupiec's likelihood ratio,

$$\text{LR}_{\text{uc}} = -2 \ln[(1 - p)^{n-x} p^x] + 2 \ln[(1 - x/n)^{n-x} (x/n)^x] \quad (5)$$

where x is the number of exceptions in n days and p is the nominal rate; independence and conditional coverage are tested as in Christoffersen (1998). Three windows are compared: a control period, 2019–2022, which contains the 2019 social unrest, the pandemic and the 2022 rate shock; the build-up, 2023–2025; and 2026 to 9 October. The control period starts in 2019 because the GARCH and exposure-adjusted models need 1,000 days of history. One-month VaR is evaluated on non-overlapping calendar months: the VaR available on the last business day of a month is compared with the sum of daily returns in the following month. Serial dependence is measured with the Lo–MacKinlay variance ratio and its heteroskedasticity-robust statistic (Lo & MacKinlay, 1988),

$$\text{VR}(q) = \text{Var}(r_t + \dots + r_{t-q+1}) / [q \text{Var}(r_t)] \quad (6)$$

For H4, the US duration of each AFP's Fund E is estimated over July 2025 – March 2026, before the regulatory announcement and the main losses, and correlated with the January–September 2026 real loss. With seven AFPs, the p-value of the Spearman correlation is computed exactly over all $7! = 5,040$ orderings. Finally, the January–September 2026 nominal return is attributed to the factors of Eq. (1) using, for each day, coefficients estimated up to the previous day.

6. Results

6.1 H1: the funds became long US duration

Table 2 and Fig. 1 report the exposure estimates. Until 2022, Fund E's sensitivity to US yields was small and not significant: 0.2 years in 2016–2019 and 0.9 years in 2019–2022. It rose to 1.7 years in early 2023, 4.3 years from September 2023 to 2024, 6.6 years in 2025 and 7.2 years in 2026. In the pooled model, the change between 2016–2022 and 2025–2026 is 6.26 years (standard error 0.55, $z = 11.4$). Funds C and D show the same pattern, with changes of 5.76 years ($z = 10.1$) and 5.98 years ($z = 12.1$). With the thirty-year yield, the change for Fund E is 5.92 years ($z = 10.0$).

Table 2
Effective duration of Fund E (system) by period, in years

Period	Days	US duration (10y)	Chile peso 10y	Chile UF 10y	R ²	US duration (30y)
Jan 2016 – Sep 2019	872	0.23 (0.24)	0.50 (0.26)	0.50 (0.19)	0.08	0.16 (0.22)
Oct 2019 – Dec 2022	813	0.86 (0.54)	0.37 (0.34)	0.74 (0.46)	0.09	0.54 (0.55)
Jan – Aug 2023	160	1.66 (0.76)	–1.00 (0.78)	0.62 (0.42)	0.30	1.95 (0.72)
Sep 2023 – Dec 2024	302	4.32 (0.46)	0.84 (0.37)	0.81 (0.32)	0.55	4.69 (0.48)
2025	241	6.62 (0.44)	0.91 (0.70)	0.10 (0.66)	0.63	6.41 (0.51)
Jan – 9 Oct 2026	190	7.21 (0.68)	1.33 (0.57)	1.61 (0.62)	0.49	6.37 (0.76)
Notes: Estimates of Eq. (2) from Eq. (1); Newey–West standard errors (five lags) in parentheses. US duration is the sum of the contemporaneous and lagged coefficients on the US ten-year yield (last column: thirty-year yield). Chile peso and UF columns are the durations to the ten-year local yields.						

Table 2
b. US effective duration by fund type, in years

Period	Fund C	Fund D	Fund E
Jan 2016 – Sep 2019	–1.26 (0.39)	–0.36 (0.31)	0.23 (0.24)
Oct 2019 – Dec 2022	0.07 (0.49)	0.56 (0.52)	0.86 (0.54)
Jan – Aug 2023	1.40 (0.50)	1.69 (0.61)	1.66 (0.76)
Sep 2023 – Dec 2024	3.10 (0.37)	4.17 (0.39)	4.32 (0.46)
2025	5.37 (0.51)	6.25 (0.38)	6.62 (0.44)
Jan – 9 Oct 2026	5.71 (0.83)	6.19 (0.57)	7.21 (0.68)
Notes: As Table 2, US ten-year yield, asset-weighted system return of each fund type.			

The rolling estimates show that exposure began to rise in late 2022, before the swap position recorded by the Central Bank, and accelerated from late 2023. The earlier part is consistent with purchases of foreign bonds

as US yields rose; the later part with the swap build-up. The estimate peaks above eight years in early 2026 and declines from mid-2026 as positions are reduced ahead of the new limit. Over July 2025 – March 2026, Fund E behaved like a US Treasury portfolio of about eight years’ duration, in addition to its local fixed-income holdings. H1 is supported.

6.2 Attribution of the 2026 loss

Table 3 attributes the January–September 2026 nominal return. For the system, US rates contributed – 7.88 percentage points to a nominal log return of – 6.50. Chilean UF yields contributed – 1.21 and peso yields – 0.42; the exchange rate added + 0.40, and carry and the unexplained residual + 2.61. The pattern is the same in every AFP, and with a 250-day estimation window the US contribution is – 7.91. The 2026 loss was overwhelmingly a US rate shock transmitted through the funds’ exposure, not a local one. The real loss is larger than the nominal one because the UF rose during the period.

Table 3
Attribution of the January–September 2026 nominal return of Fund E, percentage points

AFP	Total (nominal, log %)	US rates	Chile UF rates	Chile peso rates	Exchange rate	Carry and residual
System	–6.50	–7.88	–1.21	–0.42	0.40	2.61
Capital	–6.78	–7.66	–1.26	–0.40	0.46	2.07
Cuprum	–6.54	–7.72	–1.16	–0.40	0.24	2.50
Habitat	–6.17	–8.07	–1.28	–0.45	0.39	3.24
Modelo	–7.13	–8.80	–1.17	–0.38	0.62	2.60
Planvital	–6.29	–7.81	–1.17	–0.40	0.35	2.74
Provida	–6.43	–7.68	–1.15	–0.41	0.43	2.39
Uno	–6.03	–7.40	–1.17	–0.41	0.36	2.59
Notes: Daily contributions use coefficients of Eq. (1) estimated on the previous 126 days, summed over 2 January – 30 September 2026. Carry and residual is the total minus the factor contributions.						

6.3 H2: daily VaR did not fail

Table 4 reports daily backtests at 99%. In the control period every model failed: HS-250 had 30 exceptions against 10 expected and the normal model 36; even GARCH-t and filtered historical simulation had about twice the nominal rate. In 2023–2025 all models passed. In 2026, the models had between three and six exceptions against 1.95 expected. Only RiskMetrics rejects unconditional coverage at 5% (six exceptions, $p = 0.019$); the normal model and filtered historical simulation are borderline ($p = 0.067$), and HS-250 and GARCH-t pass ($p = 0.484$). None rejects independence. The 95% results (Appendix Table A1) are similar.

Table 4
Daily backtests of 99% VaR, Fund E (system)

Window	Model	Days	Exceptions	Expected	p (UC)	p (IND)	p (CC)	Mean VaR (%)
2019–2022	HS-250	999	30	10.0	< 0.001	< 0.001	< 0.001	1.11
2019–2022	Normal-250	999	36	10.0	< 0.001	< 0.001	< 0.001	0.92
2019–2022	EWMA ($\lambda = 0.94$)	999	18	10.0	0.022	0.039	0.009	0.93
2019–2022	GARCH(1,1)-t	992	21	9.9	0.002	0.076	0.002	0.95
2019–2022	FHS	992	17	9.9	0.040	0.031	0.012	0.98
2019–2022	Exposure-adjusted	932	31	9.3	< 0.001	< 0.001	< 0.001	1.04
2023–2025	HS-250	743	10	7.4	0.368	0.601	0.582	1.00
2023–2025	Normal-250	743	8	7.4	0.836	0.676	0.897	1.02
2023–2025	EWMA ($\lambda = 0.94$)	743	10	7.4	0.368	0.601	0.582	0.95
2023–2025	GARCH(1,1)-t	743	4	7.4	0.166	0.835	0.374	1.10
2023–2025	FHS	743	4	7.4	0.166	0.835	0.374	1.00
2023–2025	Exposure-adjusted	703	8	7.0	0.719	0.074	0.190	1.08
2026	HS-250	195	3	2.0	0.484	0.759	0.747	0.98
2026	Normal-250	195	5	2.0	0.067	0.607	0.163	0.85
2026	EWMA ($\lambda = 0.94$)	195	6	2.0	0.019	0.536	0.054	0.79
2026	GARCH(1,1)-t	195	3	2.0	0.484	0.759	0.747	0.97
2026	FHS	195	5	2.0	0.067	0.607	0.163	0.85
2026	Exposure-adjusted	190	1	1.9	0.471	0.918	0.767	1.20
Notes: Exceptions are days with a real return below – VaR. p (UC): Kupiec unconditional coverage; p (IND): Christoffersen independence; p (CC): conditional coverage. Mean VaR in per cent of the fund. The 2026 window ends on 9 October.								

The same holds AFP by AFP (Table 7): the standard models had between two and seven daily exceptions in 2026, with rejections at 5% only for some models in some AFPs. H2 is not supported. The 2026 loss did not come from extreme days. Daily volatility was lower than in the preceding years, and the worst day of 2026 would not have been an exception for most models. A supervisor relying on daily VaR backtests would have seen a model that worked.

6.4 Exploratory: the one-month horizon

Table 5 evaluates one-month VaR. When daily VaR is scaled by $\sqrt{21}$, every standard model under-covers monthly losses in the control and build-up periods. At 99%, the expected number of monthly exceptions is 0.48 in 2019–2022 and 0.36 in 2023–2025; the models had between three and six, and between two and five. In 2026 each standard model had one exception, September, which with ten months is not significant ($p = 0.089$). The exposure-adjusted measures had none in 2026, but they also under-covered in the earlier periods.

Table 5
One-month 99% VaR, Fund E (system): exceptions / expected (Kupiec p-value)

Model	2019–2022 (48 m)	2023–2025 (36 m)	2026 (10 m)
HS-250 $\times \sqrt{21}$	3 / 0.48 (p 0.014)	4 / 0.36 ($p < 0.001$)	1 / 0.10 (p 0.089)
Normal-250 $\times \sqrt{21}$	3 / 0.48 (p 0.014)	2 / 0.36 (p 0.056)	1 / 0.10 (p 0.089)
EWMA $\times \sqrt{21}$	4 / 0.48 (p 0.001)	5 / 0.36 ($p < 0.001$)	1 / 0.10 (p 0.089)
GARCH-t $\times \sqrt{21}$	6 / 0.47 ($p < 0.001$)	4 / 0.36 ($p < 0.001$)	1 / 0.10 (p 0.089)
FHS $\times \sqrt{21}$	6 / 0.47 ($p < 0.001$)	5 / 0.36 ($p < 0.001$)	1 / 0.10 (p 0.089)
Exposure-adjusted $\times \sqrt{21}$	3 / 0.44 (p 0.010)	4 / 0.36 ($p < 0.001$)	0 / 0.10 (p 0.654)
Exposure-adjusted, 21-day	3 / 0.44 (p 0.010)	4 / 0.36 ($p < 0.001$)	0 / 0.10 (p 0.654)
Notes: Non-overlapping calendar months. VaR on the last business day of month m is compared with the real return of month $m + 1$. Standard models are scaled by $\sqrt{21}$; the 21-day exposure-adjusted VaR uses overlapping 21-day factor moves (Eq. 4).			

Serial dependence explains part of the earlier under-coverage. Table 6 shows positive and significant variance ratios in 2016–2025: at 21 days, 2.83 in 2016–2019, 1.76 in 2019–2022 and 1.78 in 2023–2025, all with $p < 0.01$. In such conditions square-root-of-time scaling understates monthly risk, as expected (Danielsson & Zigrand, 2006; Getmansky et al., 2004). From July 2025 onwards, however, the variance ratio is not significant ($VR(21) = 1.24$, $p = 0.41$). As the US component, which trades in a deep market, came to dominate the fund's return, the return became closer to serially independent. The 2026 under-coverage therefore cannot be explained by autocorrelation. It comes from the window.

Table 6
Lo–MacKinlay variance ratios, Fund E (system) daily real return

Period	Days	VR(5)	VR(10)	VR(21)	z*(21)	p (21)
Jan 2016 – Sep 2019	872	1.84	2.29	2.83	6.83	< 0.001
Oct 2019 – Dec 2022	813	1.66	1.81	1.76	2.75	0.006
2023–2025	703	1.50	1.57	1.78	3.37	< 0.001
Jul 2025–9 Oct 2026	312	1.17	1.30	1.24	0.82	0.412
Notes: z*(21) is the heteroskedasticity-robust statistic for q = 21; p is two-sided.						

6.5 H3: the gap between volatility and exposure

Figure 3 plots the one-month 99% VaR forecasts against realised monthly losses. In mid-2023, before the swap build-up, the exposure-adjusted measure was below the scaled HS-250 measure (ratio 0.62 at the end of August 2023). During the build-up it rose above it, and in 2025 the two converged as the high volatility of early 2025 entered the 250-day window. In 2026 they separated. By the end of June 2026 the scaled HS-250 VaR had fallen to 3.49% of the fund, its lowest level since early 2024, because the volatile days of April 2025 had dropped out of the window. On the same date the 21-day exposure-adjusted VaR was 7.43%, its highest month-end level since January 2022, a ratio of 2.13. The divergence was largest in the two months before the July and September losses.

For September 2026, the VaR available at the end of August was 4.16% (HS-250 $\times \sqrt{21}$), 3.35% (GARCH-t $\times \sqrt{21}$) and 6.73% (exposure-adjusted, 21 days); the realised loss was 5.05%. Table 7 shows the same result in every AFP: the standard measures ranged from 3.17% to 4.63% and the realised September loss from 4.67% to 5.38%, so every standard measure was exceeded in every AFP, while the exposure-adjusted measure, between 6.45% and 7.35%, covered the loss in all seven. Appendix Table A2 shows that this does not depend on the window choices: across nine combinations of exposure window (63, 126 or 250 days) and history (500, 1,000 or 1,500 days), the end-of-August exposure-adjusted VaR ranged from 5.14% to 6.83%, above the realised loss in every case.

H3 is supported descriptively. The comparison rests on one large month and ten months of 2026, so it is not a statistical test of superiority, and the exposure-adjusted measure also under-covered monthly losses in 2019–2025 (Table 5). Its advantage is specific: when exposure changes faster than the return history, a measure that uses current exposure reacts and a measure that uses past returns does not.

6.6 H4: differences across AFPs

Table 7 and Fig. 4 compare the AFPs. Pre-shock US duration ranged from 7.71 years (Uno) to 9.04 years (Modelo), and the January–September real loss from 9.91% to 10.93%. The ordering of the extremes matches the hypothesis: Modelo had the highest exposure and the largest loss, Uno the lowest exposure and the smallest loss. Overall, however, the Spearman correlation is 0.50 with an exact one-sided p-value of 0.133 over the 5,040 orderings; the Pearson correlation is 0.72 (two-sided p = 0.068). H4 is not supported at conventional levels. With seven AFPs and exposures concentrated between 7.7 and 9.0 years, the test has little power; the main result is how similar the AFPs were.

Table 7
AFP-level results, Fund E

AFP	US duration Jul 2025–Mar 2026	Real loss Jan–Sep 2026 (%)	Daily exc. HS-250	Daily exc. GARCH-t	Daily exc. Exposure-adj.	Sep VaR HS-250 × $\sqrt{21}$	Sep VaR GARCH-t × $\sqrt{21}$	Sep VaR Exposure-adj. 21-day	Sep 2026 return (%)
Capital	8.00	10.76	5	3	1	4.22	3.41	6.56	–5.38
Cuprum	8.13	10.43	4	3	1	3.92	3.37	6.67	–5.05
Habitat	8.11	10.02	2	3	0	4.14	3.26	6.92	–4.89
Modelo	9.04	10.93	4	4	1	4.63	3.36	7.34	–4.67
Planvital	8.02	10.10	5	5	0	4.03	3.45	6.63	–4.95
Provida	8.00	10.35	4	2	1	3.88	3.46	6.51	–5.13
Uno	7.71	9.91	5	5	1	3.81	3.17	6.44	–4.77
Notes: US duration from Eq. (1) estimated on July 2025 – March 2026. Daily exceptions: 99% VaR, 2026. Sep VaR: one-month 99% VaR available at the end of August 2026; September was the worst month of 2026 for every AFP.									

7. Discussion

The results describe a gap between two things that VaR is often assumed to measure together: how volatile a portfolio has been and how exposed it is now. In 2026 these came apart. The fund’s daily volatility was moderate, its daily VaR met its coverage, and its one-month VaR, scaled from the daily one, was falling. At the same time its exposure to a single foreign rate was at a record. The duration gap of the title is the difference between the duration the fund carried and the duration its own return history implied.

Three implications follow. First, for supervision, a VaR limit calibrated on the fund’s own returns would not have constrained the position, because the measure was at a low point when the exposure was at a high one. The regulator’s choice of a stress-based limit on the derivatives portfolio (Superintendencia de Pensiones, 2026) addresses exactly this weakness, since it is computed from the current positions rather than from past returns. This supports earlier warnings that VaR limits for pension funds can behave like volatility limits (Berstein & Chumacero, n.d.) and that short-horizon risk measures can mislead long-term investors (Shi & Werker, 2012).

Second, for risk management, the exposure-adjusted measure is simple to compute from public data and requires no position-level information. Its value lies less in its own coverage, which was poor in earlier periods, than in the ratio between it and a volatility-based measure. A ratio of two, as in June 2026, signals that exposure has outrun the return history, whatever the absolute level.

Third, for members, the episode shows that the label of a fund type does not describe its exposure. Fund E is presented as the conservative option and is the default for members close to retirement. In 2026 it carried

more US interest-rate risk than any period in its history, and the losses fell on the members with the least time to recover. Whether the position was a reasonable investment decision is a separate question that this article does not answer: the same exposure produced gains when US rates were expected to fall, and the evaluation of a strategy by its worst outcome is a form of hindsight. The question here is narrower: whether the standard risk measure would have shown the size of the bet. It did not.

8. Limitations

The analysis uses public returns, not positions. Exposure is inferred from co-movement with yields, so it measures the economic exposure of the whole fund, including foreign bonds, and cannot separate swaps from cash bonds. The estimates are noisy on short windows, and the local yields contain gaps filled for up to three days. The exposure-adjusted VaR assumes that the systematic and idiosyncratic parts are independent and uses a single US tenor; a full position-level model would be more accurate. The 2026 sample contains ten months, so monthly comparisons are descriptive. The AFPs' internal risk models and the exact stress scenarios of the new limit are not public, so the article cannot test the regulatory measure itself. The losses reported for derivatives come from press reports of regulatory data and are cited as such; the article's own estimates are based only on fund unit values. Finally, the study period ends on 9 October 2026, while positions were still being reduced.

9. Conclusion

Between 2023 and 2026 Chile's most conservative pension fund acquired about seven years of duration to US interest rates. When US yields rose in 2026 the fund lost about a tenth of its real value, and almost all of the loss can be traced to that exposure. Daily VaR models did not fail in the formal sense; the one-month measures that scale them were at their lowest just before the largest losses. A measure based on current exposure gave twice the warning. The lesson is not that VaR is wrong but that it answers a different question: it describes how a portfolio has behaved, not what it is exposed to. When exposure is built quickly and quietly, the two diverge, and the stress-based limit adopted in April 2026 is a response to that divergence.

Declarations

Data availability. All data used are public. The replication package, with the raw data files, scripts, derived data, tables, figures, Scopus queries and a SHA-256 manifest, is deposited in Zenodo: <https://doi.org/10.5281/zenodo.23376420>. Pension fund data are from the Superintendencia de Pensiones; exchange rate, UF and Chilean yields are the property of the Central Bank of Chile and are redistributed under its terms of use, which allow reproduction with attribution; US Treasury yields are from FRED, Federal Reserve Bank of St. Louis.

Code availability. Python scripts (01–06) reproduce every number, table and figure from the raw files; two Windows batch files download the raw data again. A clean re-run reproduced all 49 output files byte for byte. Code is in the Zenodo deposit: <https://doi.org/10.5281/zenodo.23376420>.

Competing interests. The author declares no competing interests.

Funding. This research received no external funding.

Ethics. Not applicable: the study uses aggregate public financial data and involves no human participants.

Use of generative AI. The author used Claude Opus 5.5 (Anthropic) to write and debug the data-processing and estimation code, to run the analysis, to search and check the literature and press sources, and to draft and edit the text in English. It was used to speed up programming and writing in a second language. All hypotheses, design choices and interpretations were reviewed and approved by the author, every number was reproduced from the code and the raw data, and every reference was checked against its source. The author takes full responsibility for the content.

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Figures

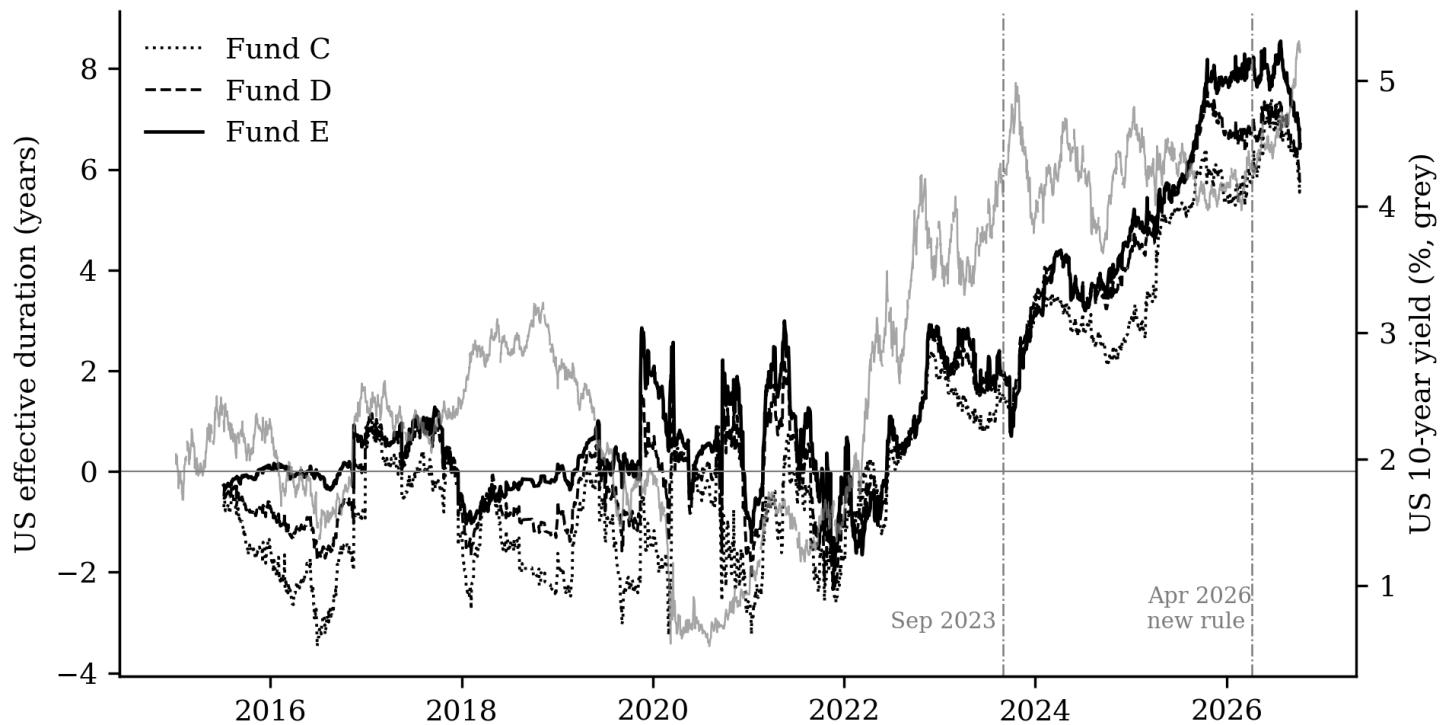


Figure 1

US effective duration of Funds C, D and E (system), 126-day rolling estimates of equation (2), and the US ten-year yield (grey, right axis). Vertical lines: September 2023 and the April 2026 derivatives rule.

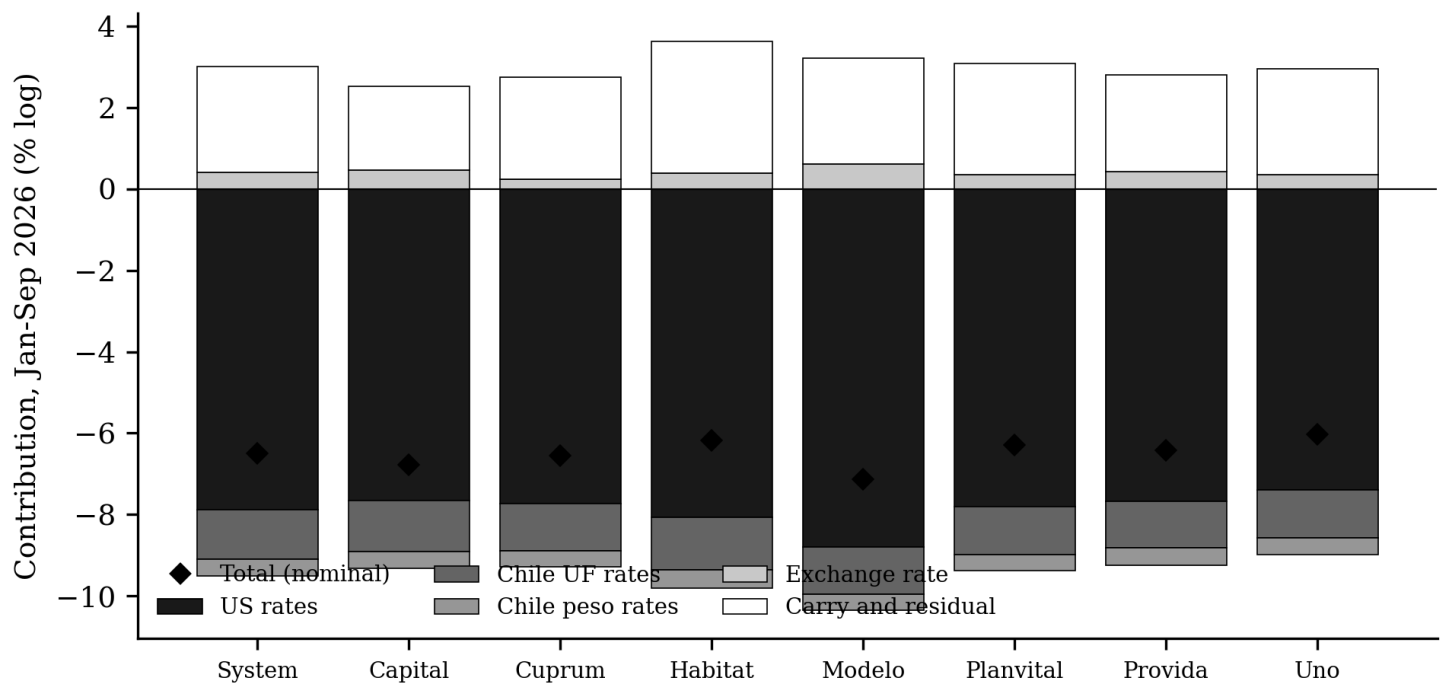


Figure 2

Attribution of the January–September 2026 Fund E return by risk factor, system and AFPs (diamonds: total nominal log return).

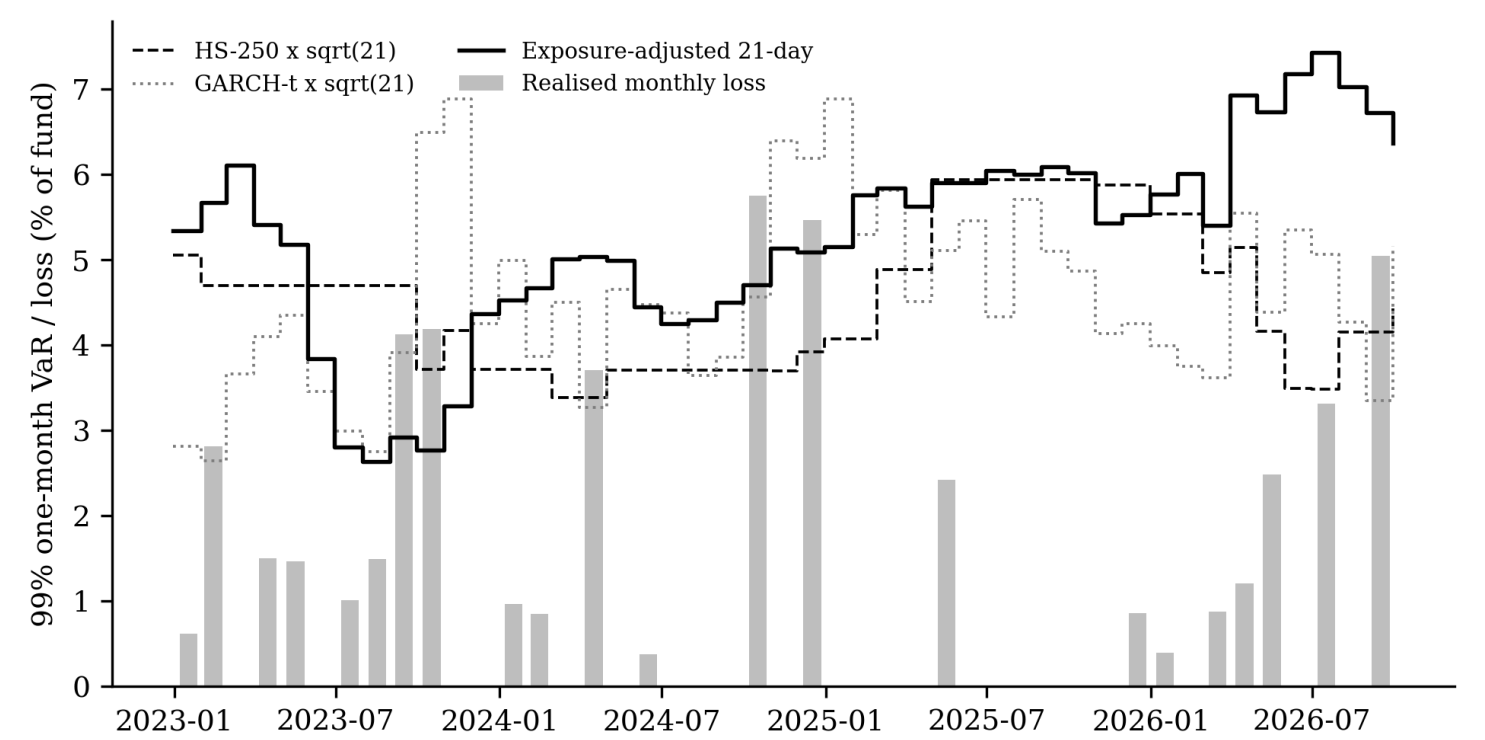


Figure 3

One-month 99% VaR forecasts and realised monthly losses, Fund E (system). Each step shows the VaR available at the end of a month for the following month.

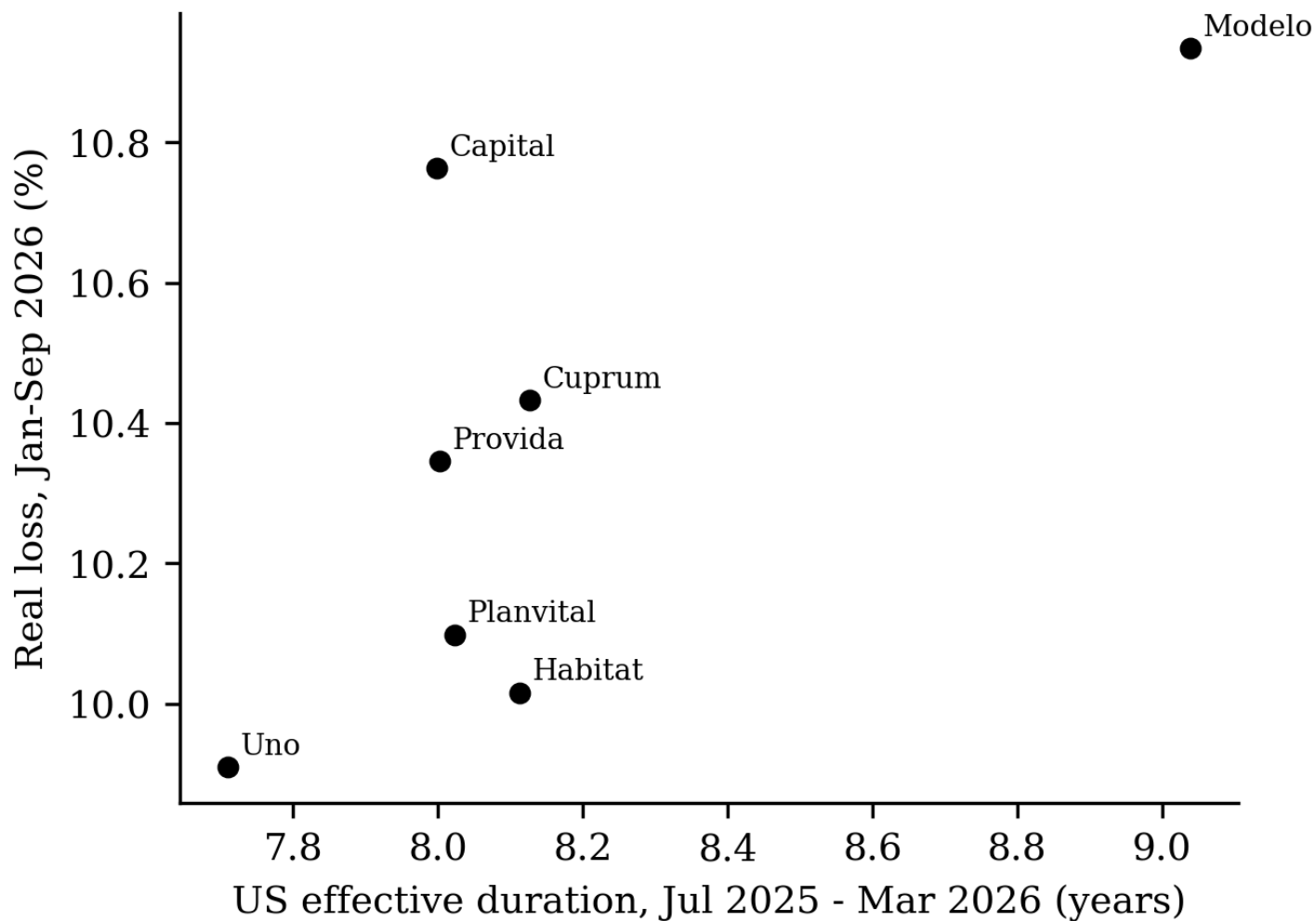


Figure 4

Pre-shock US effective duration and January–September 2026 real loss of Fund E, by AFP.

Supplementary Files

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