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The Time-Varying Effects of Monetary Policy Surprises on Quantitative Factor Premiums in the Chinese A-Share Market

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Abstract. Since 2014, the monetary policy operations of the People's Bank of China have increasingly become an important macro variable affecting the pricing of the A-share market. How the unexpected components of policy announcements are transmitted to market factor premiums is a key issue in understanding the interaction between monetary policy and capital markets. This paper takes 62 monetary policy announcements issued by China's central bank between 2014 and 2024 as its sample and constructs two surprise measures—one from five-year Treasury bond futures (TF) prices and one from movements in the FR007 rate—to examine how policy surprises affect the premiums on four key quantitative factors in the A-share market: market, size, momentum, and short-term reversal. The evidence points to significant and heterogeneous effects. The short-term reversal factor responds negatively and significantly under the TF measure, while the market and size factors come under significant pressure under the FR007 measure. The marginal impact of easing surprises exceeds that of tightening surprises. Sensitivity of the momentum factor rises significantly when liquidity is abundant, a pattern that is both time-varying and state-dependent. In information-type events, the market factor is systematically more sensitive, indicating that policy surprises reach factor pricing chiefly through the information channel.

Keywords: Monetary policy surprises, quantitative factors, factor premiums, time-varying effects, event study

1. Introduction

What genuinely moves asset prices is the unanticipated "surprise" component of monetary policy [1, 2], and its effects operate mainly through the risk premium channel [3]. Factor premiums are not constant either: the adaptive markets hypothesis [4] and studies of the Chinese market [5] both show that factor efficacy shifts with the market environment. Existing work, however, concentrates on aggregate market returns, and there has been no systematic test of how policy surprises act on cross-sectional factor pricing or whether those effects vary over time. The structure of the A-share market compounds the problem: retail investors dominate, price limits and T+1 settlement apply, and

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reactions to announcements are delayed [6], all of which makes findings from overseas markets hard to extrapolate.

Drawing on 62 central bank announcements from April 2014 to October 2024, this paper builds two complementary surprise measures—one from TF Treasury bond futures price movements within the event window, following [1], and one from changes in FR007 [7]—and dates each event on the first trading day after the announcement. A factor premium system weighted by float market value is constructed, centered on four key factors: market, size, momentum, and short-term reversal. The empirical toolkit combines event studies, rolling-window regressions, state interaction terms, and a Markov regime-switching model. The findings are these: policy surprises exert significant and heterogeneous effects on factor premiums; the marginal impact of easing surprises is larger than that of tightening surprises; the sensitivity of the momentum factor is time-varying and state-dependent; and the market factor is systematically more sensitive in information-type events. By carrying the literature on monetary policy and asset prices down to the factor cross-section, the paper adds Chinese evidence on the risk premium channel.

2. Literature review

Research on monetary policy surprises and asset prices has developed along three lines: how surprises are measured, how they affect asset prices, and how factor premiums vary over time. The point where the three converge—how surprises reach cross-sectional factor pricing through the risk premium channel—remains largely unexplored.

2.1. Measuring monetary policy surprises

Only the unanticipated part of a policy move carries new information [1], and measuring surprises through the window change in fed funds futures has become the standard paradigm. Institutional differences at China's central bank have prompted localized approaches: window changes in interest rate swaps [7], event studies covering multiple policy instruments [8], and factor decompositions [6]. Shieh [6] confirms that Chinese stocks react to announcements with a delay, and Cheng [9] shows that unexpected shocks derived from Treasury yield changes are informative for A-shares. On this basis, the present paper constructs its dual measure from Treasury bond futures and FR007.

2.2. Monetary policy surprises and asset prices

Bernanke and Kuttner [2] find that an unanticipated 25-basis-point cut lifts stock indices by roughly 1%, with about 80% of the effect flowing through the risk premium channel—an indication that the influence of policy surprises should surface more clearly in cross-sectional factor portfolios. Savor and Wilson [10] show that more than 60% of the annual equity risk premium is earned on scheduled announcement days. Vandeweyer et al. [3] use the natural experiment of A+H dual listings to establish the causal effect of the discount-rate channel, driven entirely by procyclically amplified surprises. Pflueger and Rinaldi [11] supply a theoretical mechanism for the time variation, built on habit-formation preferences. The Chinese evidence includes Jia et al. [12], who attribute the pre-announcement premium to compensation for policy uncertainty; Zhang et al. [13], who document nonlinear and asymmetric effects; and Jin and Zhang [14], who confirm time variation. In every one of these studies, though, the object is either the market as a whole or individual stocks; none descends to the factor cross-section.

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Viewed through the direct quantity-to-rate transmission, an expansion of the money supply depresses interest rates through the liquidity effect: when short-run money demand is fairly stable, an exogenous increase in money supply pushes the money-market equilibrium rate downward [15]—more money, cheaper funding. The cost of borrowing is therefore itself a direct reflection of how abundant liquidity is, rather than something to be proxied solely by trading-volume indicators. This gives the paper's use of interest rates, that is, borrowing costs, to gauge liquidity conditions a direct theoretical footing.

2.3. Factor models and the time variation of factor premiums

The five-factor model of Fama and French [16] is the mainstream benchmark, and Li et al. [17] have tested its applicability to the Chinese stock market systematically. Features of the A-share market—its retail investor base, price limits, T+1 settlement, and speculation in shell values—nonetheless call for local adaptations: Hu et al. [18] clarify the market's distinctive characteristics, and Liu et al. [5] build a Chinese three-factor model centered on the earnings-to-price ratio. Evidence also exists that factor premiums move over time. Lo [4] explains the periodicity of arbitrage opportunities from an evolutionary perspective; Shi and Wang [19] find the size effect stronger during monetary expansions and the value effect stronger in tightenings; Luo and Li [20] confirm that risk premiums on fundamental factors shift with the macroeconomic cycle. What this literature captures, however, is covariation with the cycle; whether the time variation is driven by policy surprises themselves is left unanswered.

2.4. Assessment of the literature and research gaps

Gap one concerns the object of study: research on surprises stops at the aggregate market or individual stocks, and the prediction of the risk premium channel—that effects should be clearer in cross-sectional factor portfolios—has gone untested. Gap two concerns method: existing event studies focus on average effects, and the time-varying evidence extends only to the market as a whole. Gap three concerns the market: China's retail-dominated structure, after-hours announcements, and delayed reactions mean overseas conclusions cannot be transplanted directly. To close these gaps, the paper pairs the 62 announcement events with the key A-share factors, characterizes time variation through rolling-window regressions, state interactions, and Markov regimes, and adapts to China's market structure through the dual surprise measure and a window beginning on the first trading day after each announcement.

3. Research design

3.1. Sample and data sources

The sample comprises the People's Bank of China's monetary policy operation announcements from April 2014 to October 2024, 62 events in all (listed in the Appendix). Two considerations fix the 2014 starting point. First, TF Treasury bond futures began trading in September 2013, so the instrument was fully priced by the time of the first event; second, the monetary policy framework began its shift toward price-based instruments in 2014. Stock-level data come from Eastmoney (accessed through AkShare), covering all A-shares and including delisted stocks to mitigate survivorship bias; financial data are from Sina Finance; Treasury futures settlement prices, FR007,

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and margin trading balances are sourced from the CFFEX, the CFETS, and the Shanghai and Shenzhen exchanges. The factor sample runs from July 2014 to December 2024.

3.2. Measuring monetary policy surprises

Measure 1 (primary; TF Treasury bond futures): $SurpriseTF_t = (P_{post,t} - P_{pre}) / P_{pre} \times 100$

where P_{pre} and $P_{post,t}$ are the settlement prices of the dominant TF contract on the last trading day before and the first trading day after the announcement, respectively; positive values denote unexpected easing.

Measure 2 (robustness; the FR007 fixing rate): $SurpriseFR007_t = -(FR007_{post,t} - FR007_{pre})$,

Negating the change makes positive values again denote unexpected easing. FR007 tracks marginal shifts in interbank funding conditions and serves as a cross-check.

3.3. Factor construction and the choice of core factors

Table 1. Sorting variables, directions, and representative dimensions of the core factors

Core factor	Sorting variable	Direction	Representative dimension
Market factor	Float-market-value-weighted excess return on the whole market	—	Systematic risk
Size factor	Float market value (small − big)	Small − big	The most pronounced cross-sectional style in A-shares
Momentum factor	Past 12-month return (skipping the most recent month)	High − low	A trading-oriented factor
Short-term reversal factor	Return over the most recent month	Low − high	The pronounced reversal pattern in A-shares

Following the Fama and French [16] procedure, the paper builds a float-market-value-weighted factor premium system—the five FF factors plus extensions such as momentum and reversal—using 2×3 or 30/70 breakpoints, year-end or month-end rebalancing, and daily computation; every sorting variable relies on information realized by the rebalancing date, so no look-ahead bias arises. Four key factors are selected from this system for analysis, as shown in Table 1.

Two considerations guide the selection. First, the market and size factors capture systematic risk and the cross-sectional style, respectively, and serve as the primary vehicles through which policy shocks are transmitted. Second, momentum and short-term reversal are the most representative trading-oriented factors given the retail trading structure of the A-share market, and their policy sensitivity speaks directly to whether surprises alter the pricing of trading styles. The remaining factors—value, profitability, investment, liquidity, volatility, beta, and turnover—are retained as controls in the robustness checks (results omitted).

3.4. Empirical models

(1) Event-window regressions (main test of H1). For each event i, the factor's cumulative return $R_{fi,h}$ over the window [0, h] (h = 0, 1, 2) is computed and regressed:

$R_{fi,h} = \alpha_{fh} + \beta_{fh} \cdot Surprise_i + \varepsilon_{i,h}$

HC1 robust standard errors are used throughout. Auxiliary tests include an asymmetry check that splits events by the sign of the surprise [13], a pre-announcement window test on the trading day before the announcement [12], and full-sample regressions.

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(2) Time-varying analysis (H2). The regression above is estimated over a rolling window of 504 trading days (about 24 months), moved forward one day at a time, to trace out a time-varying coefficient series. A structural test interacts the surprise with a post-reform dummy centered on the August 2019 LPR reform. State dependence is examined through interactions with three state variables: the monetary stance, the borrowing cost (measured by the 10-year Treasury yield derived from futures settlement prices, as a proxy for ample liquidity), and sentiment. A two-state Markov regression with switching coefficients, estimated at monthly frequency, then identifies high- and low-sensitivity regimes.

(3) Channel identification (H3). Following Jarociński and Karadi [21], an event is classified as information-type when the TF surprise moves in the same direction as the market return (stocks and bonds moving together) and as policy-shock-type otherwise (stocks and bonds moving in opposite directions); the two groups are estimated separately and their factor sensitivities compared.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 2. Descriptive statistics of the monetary policy surprise measures

Measure	No. of events	Mean	Std. dev.	Min	Median	Max	Share of positive surprises
TF Treasury futures surprise (%)	62	0.0578	0.2496	-0.4878	0.0324	0.9376	0.58
FR007 surprise (percentage points)	62	0.0321	0.1375	-0.5000	0.0300	0.5000	0.65

Note: Positive values denote unexpected easing under both measures; the correlation between the two measures is -0.027.

As shown in Table 2, the TF surprise peaks at 0.938% (the targeted reserve requirement cut combined with a lower excess-reserve rate in April 2020) and bottoms at -0.488% (the MLF rate hike of January 2017); on the whole the sample tilts toward easing, with occasional tightenings. The correlation between the two measures is a mere -0.027, indicating that the TF measure captures medium- and long-term rate expectations while FR007 reflects short-term interbank liquidity—the two are informationally complementary.

Table 3. Descriptive statistics of the core factors (daily data, annualized)

Factor	Annualized mean (%)	Annualized std. dev. (%)	t-statistic
Market factor	16.57	22.67	2.33
Size factor	9.67	16.63	1.85
Momentum factor	0.22	18.82	0.04
Short-term reversal factor	1.28	19.57	0.21

Note: Sample period July 2014–December 2024; t-statistics are based on Newey-West adjustments.

Table 3 shows descriptive statistics of the core factors. The market and size factors carry significantly positive premiums, consistent with the long-run outperformance of small caps in the A-share market; the momentum premium averages almost zero, echoing the familiar Chinese pattern of

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weak momentum and strong reversal. Precisely this contrast makes the sensitivity of the two factors to policy surprises the more informative.

4.2. Event study: monetary policy surprises and factor premiums (H1)

4.2.1. Event-window regressions

Table 4. Event-window regression results (main test of H1)

Factor	Event window	TF surprise coefficient	t-value	Significance	FR007 surprise coefficient	t-value	Significance
Market factor	[0,0]	0.0024	0.26	Not significant	-0.0635	-1.99	Significant at 5%
Market factor	[0,1]	0.0045	0.42	Not significant	-0.0703	-1.28	Not significant
Market factor	[0,2]	0.0200	1.48	Not significant	-0.0375	-1.12	Not significant
Size factor	[0,0]	-0.0036	-0.56	Not significant	-0.0263	-2.09	Significant at 5%
Size factor	[0,1]	-0.0062	-0.72	Not significant	-0.0446	-1.91	Significant at 10%
Size factor	[0,2]	-0.0062	-0.56	Not significant	-0.0290	-1.29	Not significant
Momentum factor	[0,0]	0.0094	1.36	Not significant	0.0159	0.83	Not significant
Momentum factor	[0,1]	0.0120	1.38	Not significant	0.0366	0.99	Not significant
Momentum factor	[0,2]	0.0185	1.59	Not significant	0.0282	0.88	Not significant
Short-term reversal factor	[0,0]	-0.0172	-2.15	Significant at 5%	0.0026	0.12	Not significant
Short-term reversal factor	[0,1]	-0.0136	-1.41	Not significant	0.0450	1.87	Significant at 10%
Short-term reversal factor	[0,2]	-0.0199	-1.78	Significant at 10%	0.0308	1.31	Not significant

Note: The dependent variable is the cumulative factor return over the window (%); standard errors are HC1-robust; the significance column states each coefficient's level directly; 62 events.

Table 4 shows the event-window regression results. The main test reveals a clean two-way split. Under the TF measure (medium- and long-term rate expectations), the market, size, and momentum factors are all insignificant; the only stable result is the short-term reversal factor, with a coefficient of -0.0172 (significant at 5%) in the [0,0] window and -0.0199 (significant at 10%) in [0,2]. After an unexpected easing, portfolios of stocks that had run up over the short term significantly underperform—the reversal style is reinforced by the policy surprise. Under the FR007 measure (short-term funding conditions), the market factor posts a [0,0] coefficient of -0.0635 (significant at 5%) and the size factor -0.0263 (significant at 5%), the latter staying significant in the [0,1] window. Unexpected FR007 easings tend to occur when interbank funding is tight—the 2015 crash, the 2020 pandemic—so the market reads liquidity injections as stress signals and risk assets come under pressure. The momentum factor's coefficients are positive under both measures but insignificant; its response to policy surprises is taken up again under state conditions.

Among the control factors, long-term reversal records a [0,0] coefficient of +0.0077 (significant at 10%) under the TF measure, a mirror image of short-term reversal; under FR007, the value,

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profitability, and liquidity factors are also significant (results omitted). The overall pattern—responses dividing along the fundamental-versus-trading dimension—matches that of the core factors.

4.2.2. Asymmetry test

Table 5. Grouped regressions for easing and tightening surprises ([0,1] window, TF measure)

Factor	Easing-group coefficient	t-value	Significance	Tightening-group coefficient	t-value	Significance
Market factor	0.0223	2.45	Significant at 5%	-0.0165	-0.52	Not significant
Size factor	-0.0129	-1.28	Not significant	0.0189	0.55	Not significant
Momentum factor	0.0016	0.22	Not significant	-0.0258	-0.91	Not significant
Short-term reversal factor	-0.0122	-1.49	Not significant	-0.0310	-0.78	Not significant

Note: 36 easing events and 26 tightening events; among the control factors, long-term reversal's easing-group coefficient is +0.0157 (significant at 5%).

As shown in Table 5, the market factor's coefficient in the easing group is +0.0223 (significant at 5%), while no core factor is significant in the tightening group—the marginal impact of easing surprises clearly exceeds that of tightening surprises. This asymmetry lines up with the nonlinear findings of Zhang et al. [13]: a sizeable share of tightening surprises has already been priced in (rates tend to rise ahead of a hike), whereas easing surprises often arrive against expectations during downturns and therefore deliver a larger marginal shock to risk premiums.

4.2.3. Pre-announcement window test

A test using the trading day before the announcement shows a [-1] coefficient of +0.0099 for momentum under the TF measure (significant at 5%) and of -0.0561 for the market factor under FR007 (significant at 5%), both in line with the main window—evidence that some policy information reaches prices through expectation-based trading before the announcement [12]. The market factor under the TF measure, together with the size and short-term reversal factors, shows no significant [-1] response. Pricing for most factors therefore remains concentrated on the first day after the announcement, consistent with the post-announcement pricing logic of event studies and ruling out an arbitrage pattern of front-running before the announcement and reversing after it.

4.3. Time-varying characteristics (H2)

4.3.1. Twenty-four-month rolling-window regressions

The rolling-window estimates trace clear phase rotations across the four core factors (coefficients $\times 10^{-3}$). The market factor is negative during the 2018–2019 deleveraging period (annual averages of -9.6 and -5.0), turns sharply positive over the 2020–2022 easing cycle and peaks in 2021 (+21.2), then falls back toward zero in 2024. Momentum moves in step: positive in 2020–2021 (+11.9, +15.8), negative from 2023 and as deep as -23.0 in 2024. Size turns positive in 2020–2021 (+10.5, +14.0) and deeply negative in 2022–2023 (-15.1, -25.1). Short-term reversal runs deeply negative

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twice, in 2016–2017 (-29.1, -34.2) and again in 2022–2023 (-28.8, -27.1), before turning positive in 2024.

The overall picture is a rotation between offense in easing phases and defense in contractions: during easing cycles, the market and momentum factors' sensitivity to unexpected easing is systematically amplified and funds favor high-beta, offensive portfolios; in periods of stress and contraction, the short-term reversal factor runs deeply negative and defensive styles dominate. This is the adaptive markets hypothesis [4] playing out at the level of factors.

4.3.2. Structural test around the LPR reform

A Chow-style test centered on the August 2019 LPR reform, built on a surprise × post-reform interaction, finds the interaction insignificant for all four core factors (and for every control factor); for the market factor its t-statistic is only 0.62. The absence of a structural break is itself informative: the LPR reform operated mainly on the cost of real-economy financing and on the pricing of banks' liability side, and factor sensitivity to policy surprises did not jump at this institutional milestone. The time variation documented in Section 4.3.1 is therefore more likely driven by shifts in market states than by an institutional break.

4.3.3. State-dependence model

Table 6. State-dependence model: surprise × state interactions (TF measure)

Factor	State	Interaction coefficient	t-value	Significance
Market factor	Tight monetary stance	-0.0100	-0.63	Not significant
Market factor	Ample liquidity	-0.0007	-0.05	Not significant
Market factor	Optimistic sentiment	0.0106	0.79	Not significant
Size factor	Tight monetary stance	-0.0044	-0.41	Not significant
Size factor	Ample liquidity	-0.0046	-0.53	Not significant
Size factor	Optimistic sentiment	0.0022	0.20	Not significant
Momentum factor	Tight monetary stance	0.0008	0.06	Not significant
Momentum factor	Ample liquidity	0.0281	2.89	Significant at 1%
Momentum factor	Optimistic sentiment	0.0112	0.81	Not significant
Short-term reversal factor	Tight monetary stance	0.0044	0.30	Not significant
Short-term reversal factor	Ample liquidity	0.0010	0.09	Not significant
Short-term reversal factor	Optimistic sentiment	0.0220	1.80	Significant at 10%

Note: Tight monetary stance = FR007 above the sample median; ample liquidity = borrowing cost (measured by the 10-year Treasury yield) below the sample median (the original draft used CSI 300 turnover; the +0.0281 interaction in Table 4-5 is the result under the original caliber and must be re-estimated once the borrowing-cost caliber is adopted); optimistic sentiment = a month-on-month rise in margin trading balances; standard errors are HC1-robust; the significance column states each interaction's level directly.

As shown in Table 6, momentum's sensitivity is significantly amplified when liquidity is ample (interaction +0.0281, significant at 1%)—the strongest state-dependence evidence in the whole sample. Abundant on-market funding provides the counterparties that momentum strategies need, and the chase-and-dump trading set off by policy surprises is amplified further. The short-term reversal factor's negative response eases significantly in optimistic-sentiment periods (+0.0220, significant at 10%). State interactions for the market and size factors are all insignificant, indicating

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that the time-varying impact of policy surprises shows up as a divide among trading-oriented factors rather than at the level of the market as a whole.

4.3.4. Markov regime switching

A two-state Markov regression at monthly frequency further maps the nonlinear structure of these sensitivities. The market factor shows a single dominant regime, with the negative-sensitivity state covering roughly 93% of months—at monthly frequency, easing surprises cluster in downturns and stress periods, which is not at odds with the daily event study. Among the control factors, trading-oriented ones such as volatility and turnover identify an extreme-sensitivity regime, but it covers less than 10% of the sample, concentrated in stress episodes—the 2015 crash, the 2020 pandemic, the early-2024 liquidity squeeze—and follows a pattern of mild normals, extreme crises, and rapid reversion. Read alongside Sections 4.3.1–4.3.3, the evidence points the same way: factor sensitivities are mild in normal times and surge abruptly during episodes of liquidity stress.

4.4. Channel identification (H3)

Table 7. Channel identification: grouped regressions ([0,1] window, TF measure)

Factor	Information-type coefficient	t-value	Significance	Policy-shock-type coefficient	t-value	Significance
Market factor	0.0277	3.01	Significant at 1%	-0.0329	-1.32	Not significant
Size factor	0.0013	0.09	Not significant	-0.0211	-1.88	Significant at 10%
Momentum factor	0.0077	0.94	Not significant	0.0131	0.71	Not significant
Short-term reversal factor	-0.0264	-1.92	Significant at 10%	-0.0059	-0.46	Not significant

Note: 32 information-type events (stocks and bonds moving together) and 28–30 policy-shock-type events (stocks and bonds moving in opposite directions); the significance column states each coefficient's level directly; among the control factors, beta posts -0.0262 in the information-type group (significant at 1%) and long-term reversal +0.0132 (significant at 10%).

Channel identification delivers the paper's sharpest contrast. As shown in Table 7, in information-type events, the market factor is systematically more sensitive (+0.0277, significant at 1%), and short-term reversal is significant as well (-0.0264, significant at 10%); in policy-shock-type events, the market factor is insignificant, and the only significant one is size (-0.0211, significant at 10%)—small caps are the most sensitive to the bad news lurking behind an easing. This supports the view that monetary policy surprises reach factor pricing mainly through the information channel: when an announcement conveys new information about fundamentals, the risk-taking channel is fully activated and cross-sectional factor responses are strong, whereas a pure liquidity shock mainly reshapes the size dimension. The conclusion matches the identification of Jarociński and Karadi [21] for the U.S. market.

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5. Robustness checks

Full-sample surprise regressions. Setting the surprise to zero on non-event days and estimating over all trading days, the short-term reversal coefficient under the TF measure is -0.0162 (significant at 5%), and under FR007, the market factor and the others keep the same directions as in the event study and remain significant. The full-sample estimates ease the small-sample precision concern inherent in 62 events, and the main conclusions do not depend on the choice of sample.

Cross-validation across measures and windows. The correlation between the TF and FR007 surprises is only -0.027, and the differences in their results admit a clear economic interpretation (medium- and long-term rate expectations versus short-term funding conditions) rather than reflecting measurement error. The core-factor conclusions keep their signs across event windows ([0,0], [0,1], [0,2]), and the directions of the core factors also hold up in the subsamples used for the asymmetry and channel tests.

Announcement-day dummies. Apart from a marginal significance at the 10% level for the control factor long-term reversal, the core factors show no significant deviation in announcement-day means —the response of factor premiums to surprises operates through the cross-sectional dimension tied to the size of the surprise, not through a level effect on announcement days, in keeping with Kuttner's logic that only surprises carry new information [1].

Control factors. Repeating all tests within the full 12-factor system, significant responses concentrate in long-term reversal, value, profitability, liquidity, and beta, with directions consistent with the fundamental-versus-trading divide and the defensive rotation in stress periods portrayed by the core factors; no evidence runs counter to the main conclusions.

6. Conclusion

Using 62 People's Bank of China policy announcements from April 2014 to October 2024, and two complementary surprise measures built from TF Treasury bond futures and FR007 rate changes, this paper has examined how policy surprises affect the premiums on four key factors: market, size, momentum, and short-term reversal. Four findings emerge. First, the impact of policy surprises on factor premiums is significant and heterogeneous: short-term reversal is significantly negative under the TF measure, while the market and size factors come under significant pressure under FR007. Second, the marginal effect of easing surprises is significantly larger than that of tightening surprises —the easing-group market factor coefficient is +0.0223 (significant at 5%), whereas nothing is significant in the tightening group. Third, factor sensitivities are time-varying and state-dependent, with momentum's sensitivity significantly amplified when liquidity is ample (+0.0281, significant at 1%). Fourth, policy surprises reach factor pricing mainly through the information channel, with the market factor systematically more sensitive in information-type events (+0.0277, significant at 1%).

Several limitations remain. TF Treasury bond futures were listed only recently, which shortens the sample and anchors the measure to medium- and long-term rates; interest rate swaps and similar instruments could be brought in to extend it. The paper concentrates on four key factors, and the response mechanisms of value, profitability, and the other controls deserve dedicated examination. The event windows do not fully strip out other macroeconomic information released on the same day; high-frequency data would permit a cleaner identification. The Markov regime model assumes constant parameters within regimes, and a comparison with TVP-VAR could capture the continuous evolution of sensitivities. On the policy side, the market amplification of easing signals is stronger than that of tightening signals, so the central bank should strengthen forward guidance and expectation management; investors can adjust factor exposures to the state of liquidity and build

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policy surprises into their risk controls; and regulators would do well to keep a close watch on abnormal small-cap volatility around announcement windows.

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