Not all surprises matter: Attention and monetary transmission

David de Villiers

ERSA working paper 937

August 2026

Not all surprises matter: Attention and monetary transmission

David de Villiers[1]

This paper combines high-frequency monetary policy surprises with weekly Google search data in South Africa (2010–2026) to evaluate how central bank communication drives credit-related information acquisition. Using variation in shock magnitudes and pre-existing attention states, the results show that transmission is highly non-linear. Small policy surprises generate little measurable behavioural response, whereas large, salient shocks trigger significant credit search activity. Moreover, this behavioural response is highly conditional, heavily amplifying when baseline public attention is already elevated. This behavioural channel is concentrated within forward-looking formal credit searches, while distress-related and informal credit searches exhibit no systematic response to policy innovations. Ultimately, findings support the view that rational inattention operates as a selective filter on monetary policy transmission, suggesting that strategic central bank communication must actively navigate the public's shifting capacity to process policy surprises.

Keywords: Monetary policy surprises; rational inattention; salience; high-frequency identification; Google Trends

JEL codes: E52, D83, G41, E71

[1]*Rhodes University. Email* david.devilliers@ru.ac.za; davidjamesdevilliers@gmail.com

1. Background

Central banks rely on efficient monetary transmission to stabilise inflation while preserving financial and economic resilience (Mishkin, 1996). Yet the effects of monetary policy depend not only on changes in interest rates, but also the degree to which households allocate attention to economic information (Sims, 2003; Bordalo, Gennaioli and Shleifer, 2012). In an emerging market such as South Africa, high exposure to variable-rate debt means that changes in the policy rate quickly alter borrowing costs and household financial conditions (International Monetary Fund, 2024). However, conventional macroeconomic indicators capture these behavioural adjustments with a significant delay. This makes it difficult to observe how households process and respond to monetary policy information in real time (Friedman, 1961; Bernanke, Boivin, and Eliasz, 2005).

This paper addresses this gap using a high-frequency event study framework that combines monetary policy surprises around South African MPC announcements with weekly digital search-based measures of credit-related attention. Rather than treating attention as a passive information filter, the paper examines whether the behavioural responses to monetary policy surprises depend on prevailing attention conditions. The results show that small policy surprises generate little behavioural response, while larger and more salient surprises trigger significant increases in credit-related search activity, particularly when baseline attention is already elevated.

The paper addresses two related questions. First, do monetary policy surprises generate immediate changes in credit-related search behaviour? Second, does prevailing public attention amplify or dampen these behavioural responses?

2. What we build on

2.1 Monetary policy surprises and transmission

Early event-study literature established that monetary policy announcements causally shift the yield curve (Cook and Hahn, 1989). Kuttner (2001) showed that this transmission of monetary policy is driven almost entirely by the unanticipated – or surprised – component of the announcement, as anticipated changes are already integrated into forward-looking markets.

This led to the development of high-frequency identification (HFI) approaches that isolate exogenous monetary policy surprises within narrow announcement windows. The identification strategy relies on measuring the immediate pricing adjustments in financial derivatives around central bank announcements, under the assumption that no other confounding macroeconomic news is released within that interval.

These methods have been widely used to study the transmission of monetary policy through equity markets (Bernanke and Kuttner, 2005), bond yields and policy path expectations (Gürkaynak, Sack and Swanson, 2005), exchange rates (Gürkaynak, Hakan Kara, Kısacıkoğlu, and Lee, 2021), and broad macroeconomic transmission mechanisms (Gertler and Karadi, 2015). Moreover, Jarociński and Karadi (2020) disentangle pure structural policy surprises from central bank information surprises.

High-frequency identification approaches have increasingly been extended to emerging market economies. Cross-country evidence from emerging markets shows that monetary policy surprises remain effective in EMEs, while also highlighting important differences in the strength and channels of transmission. Checo, Grigoli and Sandri (2024) find that unexpected tightening raises bond yields, reduces real activity and lowers inflation, with stronger effects on highly leveraged firms. Beltrán (2025) shows that U.S. monetary tightening raises sovereign spreads and generates contractionary effects in EMEs through exchange-rate and financial channels. Juselius and Xia (2026) show that financial vulnerabilities shape EME responses to U.S. monetary shocks, particularly where foreign-currency debt is high and FX markets are shallow.

Country-specific evidence provides further support for the effectiveness of monetary surprises across different transmission margins. In Brazil, Meurer, Santos and Turatti (2015) find that monetary policy surprises increase the likelihood of jumps in interest rates. In China, Lu, Tang and Zhang (2023) show that unexpected monetary easing increases corporate investment. For India, Lakdawala and Sengupta (2024) find that monetary policy shocks lower bond and stock prices. Communication about the future policy path raises Malaysian medium- and long-term bond yields and corporate borrowing costs and bond yields in Malaysia (Ho and Karagedikli, 2025). In South Africa, Pirozhkova, Ricco and Viegi (2024) show that high-frequency monetary policy surprises affect the yield curve, output, prices, and country risk dynamics. Taken together, the evidence indicates that monetary policy surprises affect financial conditions, investment and real activity, with transmission shaped by country-specific financial structures.

Beyond financial markets, South African evidence suggests that monetary policy operates through household credit and balance-sheet channels. Aron and Muellbauer (2006, 2013, 2025) show that credit conditions, housing wealth, mortgage debt and non-mortgage debt play a central role in transmitting monetary policy to consumption and aggregate demand. Moreover, the high prevalence of variable-rate lending in South Africa (IMF, 2026) amplifies the cash-flow channel of monetary transmission. Aron and Muellbauer (2025) further establish that mortgage and non-mortgage debt exhibit distinct transmission dynamics, with unsecured non-mortgage debt leaving many households particularly exposed to unexpected increases in borrowing costs. Because policy surprises immediately alter debt-servicing obligations, they are likely to induce both household financial stress and information acquisition – these behaviours typically occur well before these adjustments become visible in conventional macroeconomic aggregates.

Effective monetary policy transmission also depends on central bank communication. Reid (2009) shows that South African inflation expectations are relatively well anchored to macroeconomic surprises. This credibility means that macroeconomic surprises do not cause panic or shift long-term expectations because the public trusts the bank to manage medium-term inflation. Moreover, Reid and Du Plessis (2010) find that the SARB has consistently communicated its future policy intentions through MPC statements. However, Reid and Du Plessis (2010) focus on how financial analysts interpret MPC statements, this leaves open whether households pay attention to the same announcements.

Collectively, this literature shows that monetary policy surprises generate immediate and economically significant adjustments across financial markets, expectations, and broader macroeconomic outcomes. Building on this literature, the present study examines whether monetary policy surprises also generate immediate behavioural responses observable through aggregate credit-related digital search activity.

2.2 Rational inattention and state-dependent salience

Standard macroeconomic models assume that agents continuously process macroeconomic information and fully incorporate policy announcements into expectations. However, people are rationally inattentive because information acquisition is costly and people have limited cognitive capacity, which together lead individuals to allocate attention selectively rather than continuously (Sims, 2003; Reis, 2006). When informationally constrained, individuals optimise their limited attention by prioritising information streams that exhibit higher variance or pose greater consequences for their objective functions (Mackowiak and Wiederholt, 2009) Moreover, individuals do not respond equally to all macroeconomic information, and many economic developments receive limited attention unless they become sufficiently salient or personally relevant (Gabaix, 2020).

Attention is not constant; it is endogenous to economic conditions and perceived risk. For example, people's attention to macroeconomic conditions rises during periods of elevated inflation and uncertainty (Bracha and Tang, 2025). Bordalo, Gennaioli and Shleifer (2012; 2013) find that once information becomes salient, people will sharply increase attention and overweight, the importance of the signal, amplifying short-run behavioural adjustments. In particular, households become more attentive to macroeconomic developments (Macaulay, 2025) and more responsive to policy-relevant information (Coibion et al., 2022) when their financial exposure or economic risk is high. Corroborating this, Pfäuti (2026) documents strict 'attention thresholds' where public focus remains dormant until a macro shock crosses a visible salience boundary.

These insights imply that the behavioural transmission of monetary policy surprises may itself be state dependent. While small or routine policy surprises may receive little public attention, larger unexpected announcements may trigger disproportionate information-seeking responses. This suggests that monetary policy transmission may operate not only through conventional financial channels, but also through shifts in collective attention and information acquisition behaviour.

Together, these theories imply that the transmission of monetary policy surprises may vary across attention states, particularly when policy announcements become sufficiently salient to trigger intensified information acquisition.

2.3 Digital search data and economic expectations

Online search activity is a real-time proxy of information acquisition and economic attention (Choi and Varian, 2012). Search intensity reflects revealed information demand, rather than passive media consumption, it allows researchers to observe how agents process uncertainty and news in near real time (Da, Engelberg, and Gao, 2011). Search-based indicators have subsequently been used to study behavioural responses to financial conditions, uncertainty, and macroeconomic developments.

Google Trends has become an established behavioural measure in empirical macroeconomics, with search intensity increasingly used to capture information acquisition, expectations, and latent economic activity at high frequencies. Applications of search data in a macroeconomic context span macroeconomic nowcasting (Choi and Varian, 2012; Woloszko, 2024), policy-related uncertainty (Donadelli, 2015), labour market conditions (Askitas and Zimmerman, 2009; D'Amuri and Marcucci, 2012), anticipating financial market movements (Preis, Moat and Stanley, 2013), forecast exchange rate movements (Bulut, 2017), forecasting housing market sales and price trends (Wu and Brynjolfsson, 2009) and measure financial stress (Stolbov et al., 2022; Stolbov and Shchepeleva, 2025). The diverse applications of these data highlight their ability to capture behavioural shifts before they appear in conventional administrative statistics.

More recent work applies search-based measures to macroeconomic expectations and monetary policy communication. For instance, because of rational inattention, household's salience and the response of inflation expectations to monetary policy communication are proportional to the complexity of central bank announcements (Coibion, Gorodnichenko and Weber, 2022). Individuals only update their expectations if the news is sufficiently simplified, complex communications fail to become salient with the public. Extending this logic to monetary policy transmission, Jo, Shim and Varghese (2026) construct a Google Trends-based Monetary Policy Attention index and show that the macroeconomic effects of monetary policy surprises vary across attention states. Their findings suggest that public attention may condition the transmission of monetary policy.

In the presence of costly information acquisition and search frictions, online search behaviour can therefore provide a behavioural measure of changing expectations, perceived financial conditions, and information-seeking activity before these adjustments appear in conventional macroeconomic indicators (Møller et al., 2023). Digital search data therefore provide a high-frequency behavioural measure through which shifts in collective financial attention can be observed in near real time.

3. Data and institutional context

3.1 Monetary policy surprise identification

The sample covers 2010W1–2026W19, comprising 853 weekly observations, of which 98 correspond to South African Reserve Bank (SARB) Monetary Policy Committee (MPC) announcement weeks. The SARB MPC announces policy decisions six times annually, typically on Thursdays at approximately 15:00 SAST.

Monetary policy surprises are measured using daily changes in the FRA1x4 contract (LSEG, 2026) around SARB MPC announcements (SARB, 2026). FRA contracts reflect market expectations of future short-term interest rates and are commonly used in the high-frequency monetary policy literature (such as Kuttner, 2001; Gertler and Karadi, 2015; Pirozhkova et al, 2024). The daily surprise measure is constructed as the change in the FRA1x4 rate on MPC announcement days. To align with the weekly frequency of Google Trends data (Google, 2026), daily surprises are aggregated into weekly event indicators.

Daily identification of policy surprises

Following the high-frequency identification (HFI) literature, we measure the exogenous monetary policy surprise on day $t(Surprise_t)$ using the daily change in the 1-month-forward Forward Rate Agreement 4 months out ($\Delta FRA_{1\times 4}$):

$$Surprise_t = FRA_{1\times4,t} - FRA_{1\times4,t-1}$$

Because anticipated decisions are already priced into financial markets, announcement-day changes in FRA contracts primarily capture the unanticipated 'surprise' component of monetary policy communication. This identification strategy exploits narrow announcement windows to minimise contamination from unrelated macroeconomic news.[2]

Temporal alignment to weekly cycles

To match the structural weekly cadence of Google Trends data (where each week ω begins on Sunday and ends on Saturday), daily surprises aggregated into weekly observations. For weeks containing an MPC announcement, the daily surprise is isolated; while non-MPC weeks are assigned a value of zero.

$$Weekly\ Surprise_\omega = \sum_{t \epsilon \omega} Surprise_t \times MPC\_Dummy_t$$

Aligning high-frequency monetary policy surprises to weekly search data allows the empirical analysis to isolate short-run behavioural responses immediately following unexpected policy announcements while minimising contamination from unrelated macroeconomic developments occurring outside MPC announcement windows.

Descriptives statistics of policy surprises

Table 1 reports summary statistics for the 98 SARB MPC surprises ($\Delta\mathrm{FRA}_{1\times4}$) observed over the sample period (2010W1–2026W19). Eight of these announcements were fully anticipated (0 bps), 45 produced positive surprises, and 45 produced negative surprises. Approximately 69% of announcements generated surprises smaller than 10 bps, while only 22% exceeded 10 bps in absolute magnitude.

The predominance of relatively small policy surprises suggests that most MPC decisions were largely anticipated by financial markets. Because only sufficiently large policy surprises attract widespread public attention, the distribution provides motivation for the salience-threshold framework developed below.

[2] An, Stedman and Lusompa (2025) show that daily surprise measures produce results comparable to intraday identification strategies.

Table 1: Summary statistics of monetary policy surprises

Shock	Continuous surprise ($\Delta FRA_{1\times4}$)	Large shock	Salient positive shock (> +10 bps)	Salient negative shock (< - 10 bps))
Event count	98	22	45	45
Mean	-0.0092	-0.0825	0.0733	-0.0934
Standard deviation	0.1347	0.2642	0.0672	0.1457
Minimum	-0.8000	-0.8000	0.0050	-0.8000
Maximum	0.3200	0.3200	0.3200	-0.0050

Note: Surprises are measured as daily percentage point changes in the 1-month-forward Forward Rate Agreement 4 months out ($FRA_{1\times4}$) on SARB MPC announcement days across the sample period 2010W1–2026W19. Eight MPC announcements were fully anticipated by financial markets and produced a zero surprise (0 bps).

3.2 Google search data

Google Trends data are used to construct high-frequency measures of aggregate credit-related search behaviour. Google search activity provides a revealed measure of information acquisition and economic attention in near real time (Choi and Varian, 2012; Da, Engelberg and Gao, 2011). Weekly search intensity data were collected for selected credit- and debt-related search terms using Google Trends.

Because Google Trends scales search intensity relative to the selected extraction window, weekly series were extracted separately for each calendar year using annual rolling windows and standardised within each extraction window prior to concatenation. This approach preserves within-period variation and behavioural spikes while reducing distortions arising from Google Trends' relative scaling procedure. Weekly frequency is used because it aligns with the timing of MPC announcements while remaining sufficiently granular to capture short-run behavioural responses.

Search term selection is based in part on the behavioural classification framework developed in de Villiers (2026), with terms retained based on their conceptual relevance to household credit conditions and observed search intensity within the South African context. Individual search terms are grouped into distinct behavioural channels reflecting different dimensions of credit-market attention and financial stress. The distinction strengthens identification by evaluating responses across theoretically distinct behavioural channels – isolating adjustments – rather than broad public news attention.

- The credit-demand channel captures forward-looking borrowing decisions as changes in expected interest rates alter borrowing costs and housing affordability (Mishkin, 1996; Aron and Muellbauer, 2025). Unanticipated policy adjustments prompt prospective borrowers to acquire information – searching for terms related to home loans (South African nomenclature for mortgages), bond applications, and credit scores.

This channel aims to capture the initial, latent phase of market participation that occurs prior to formal bank ledger entries or formalized borrowing agreements.

- The financial management and debt restructuring channel captures balance-sheet cash-flow adjustments as rate changes alter debt-servicing burdens on existing liabilities (Bernanke and Gertler, 1995; Aron and Muellbauer, 2025). In an economy dominated by variable-rate debt, unexpected policy rate hikes squeeze disposable income, motivating liquidity-constrained households to search for institutional debt management solutions – such as *"debt review"* or *"debt consolidation"* – to restructure household balance sheets.
- The acute financial distress channel includes searches linked to missed payments and garnishee orders.[3] This channel captures rising financial distress as higher debt-servicing obligations increase repayment difficulties among indebted households (Mian and Sufi, 2014; Aron and Muellbauer, 2025). Elevated search intensity reflects growing household financial distress following unexpected changes in borrowing conditions.
- Informal credit substitution includes searches related to payday lending and informal lenders (loan sharks, and mashonisa).[4] It captures substitution towards alternative sources of liquidity when tighter monetary conditions restrict access to formal credit. Consistent with theories of credit rationing (Stiglitz and Weiss, 1981) and evidence on the importance of informal lending networks in South Africa (Krige, 2019), elevated search intensity reflects greater reliance on informal sources of credit as access to formal borrowing becomes more constrained.

To ensure comparability across search terms, each series is standardised using z-score transformations prior to index construction. Principal Component Analysis (PCA) is then applied within each behavioural category to extract a common latent search-attention factor. Internal consistency and correlation structures are evaluated using Cronbach's alpha statistics, correlation heatmaps, and PCA loading diagnostics. The resulting indices provide standardised measures of behavioural attention across different dimensions of credit-market activity.

Prior to estimation, the behavioural indices are transformed into first differences to remove deterministic seasonality and secular growth in internet search activity associated with

[3] A garnishee order (officially termed an Emoluments Attachment Order under Section 31 of the South African Magistrates' Courts Act 32 of 1944) is a court order requiring an employer to withhold debt repayments directly from a debtor's salary on behalf of a creditor.

[4] In South Africa, mashonisa refers to informal, unregulated township moneylenders operating outside the formal financial regulatory framework established by the National Credit Regulator (NCR).

growing internet penetration. The transformation yields a stationary time series needed for regression analysis whilst preserving short-run changes in search behaviour.

Table 2 presents the statistical validation for the behavioural search channels. The correlation matrices confirm that search terms within each channel generally exhibit positive co-movement, justifying their aggregation into composite indices. The first principal component (PC1) captures between 39% and 53% of the underlying variance across the four dimensions. – confirming a dominant common signal exists. Internal consistency varies across channels, reflecting the heterogeneous nature of search behaviour and the broad behavioural scope of the constructed indices. Further details on the specific factor weights and individual term contributions are provided in Appendix Table A1.

Table 2: Construction, Internal Consistency of Behavioural Search Indices

Index	Terms and correlations					PC1 variance explained	Cronbach α
Credit demand		bond calculator	home loan	Pre-approval	credit score	45%	0.42
	bond calculator	1.000					
	home loan	0.592	1.000				
	Preapproval	-0.039	0.001	1.000			
	credit score	0.119	0.157	-0.004	1.000		
Financial management		debt review	debt consolidation	debt help		50%	0.48
	debt review	1.000					
	debt consolidation	0.414	1.000				
	debt help	0.175	0.123	1.000			
Acute distress		Garnishee	missed payment			53%	0.11
	Garnishee	1.000					
	missed payment	0.058	1.000				
Informal credit		loan shark	mashonisa	payday loan	cash loan	39%	0.47
	loan shark	1.000					
	Mashonisa	0.147	1.000				
	payday loan	0.072	0.115	1.000			
	cash loan	0.178	0.273	0.267	1.000		

Note: This table details the composition of the four Behavioural Search channels. The sub-panels display the correlation matrix between selected search terms within each dimension. PC1 variance explained denotes the proportion of variance captured by the first principal component of the index. Cronbach's alpha provides a measure of internal consistency for the grouped terms. (see Appendix Table A1 for detailed factor loadings and statistical validation). Source: Author's calculations using Google (2026).

3.3 Econometric specifications

The empirical design tests for structural non-linearities and behavioural states via two distinct models:

Model A: The Non-Linear Attention Threshold

To test whether the public ignores minor policy adjustments due to information-processing constraints, a binary threshold variable ($Large\ Surprise_{\omega}$) that triggers only when an MPC surprise exceeds $\pm 10\ basis\ points$ is constructed:

$$Large\ Surprise_{\omega} = \mathbb{I}(|Weekly\ Surprise_{\omega}| > 0.10)$$

Then baseline threshold specification is estimated as:

$$\Delta Y_{\omega} = \alpha + \beta_1 Large\ Surprise_{\omega} + \Gamma \Delta X_{\omega-1} + \varepsilon_{\omega} \quad if\ MPC\_Dummy_{\omega} = 1$$

for MPC announcement weeks only.

- ΔY_{ω} represents the weekly change in a given behavioral search index, and
- $\Delta X_{\omega-1}$ is a vector of lagged high-frequency market controls. The latter are used to address potential confounding effects and ensure that findings are driven by policy innovations rather than concurrent market panic. More specifically the daily financial market controls are the JSE All Share Index and the USD/ZAR exchange rate. All regressions are estimated using OLS with heteroskedasticity-robust standard errors.

Model B: The State-Dependent Interaction

To examine whether behavioural responses depend on prevailing attention conditions, the following interaction specification is estimated:

$$\Delta Y_{\omega} = \alpha + \beta_1 Weekly\ Surprise_{\omega} + \beta_2 Y_{\omega-1} + \beta_3 (Weekly\ Surprise_{\omega} \times Y_{\omega-1}) + \Gamma \Delta X_{\omega-1} + \varepsilon_{\omega}$$

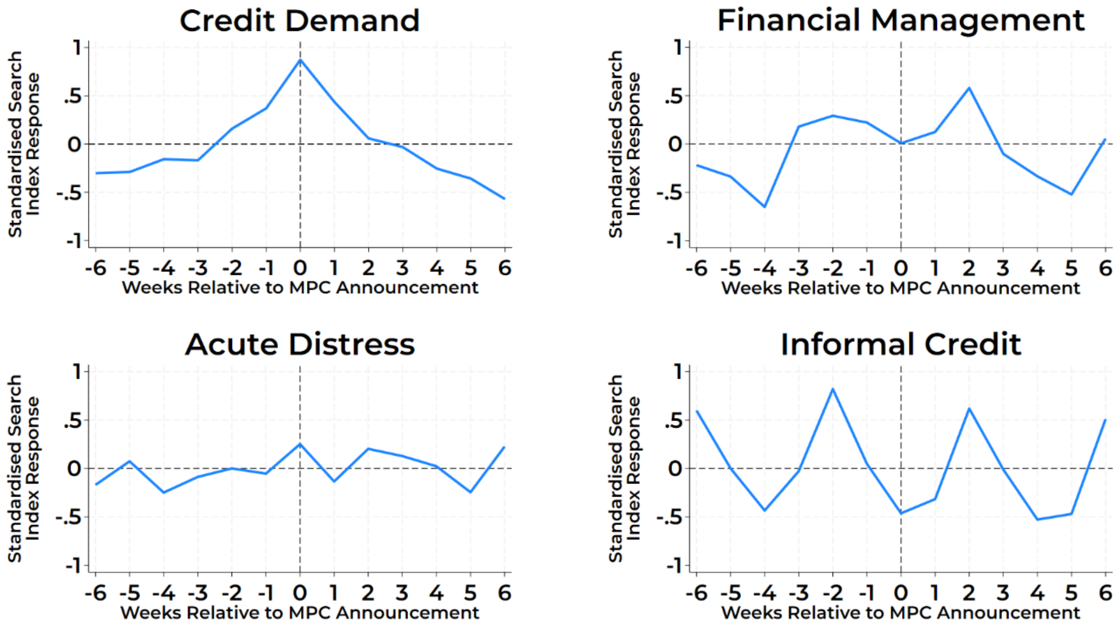
Where:

- $Y_{\omega-1}$ captures the lagged level of the behavioural search index prior to the MPC announcement. It represents the pre-existing behavioural state of attention. Using a predetermined lag mitigates contemporaneous endogeneity and simultaneous causality concerns, which ensures that baseline attention is isolated from the event-day shock.
- β_3 measures whether the effect of monetary policy surprises varies across attention states. Conceptually, this interaction term directly tests whether pre-existing market engagement lowers the marginal cost of information acquisition, thereby amplifying or dampening the transmission of immediate policy innovations. A positive interaction coefficient implies that policy surprises generate larger behavioural responses when baseline attention is already elevated.

4. Results

4.1 Event-study evidence

Figure 1: Event-study responses of behavioural search indices around monetary policy surprises.



Note: This figure presents event-study plots of the behavioural search indices constructed from Google search activity: credit demand, financial management, acute distress, and informal credit. The horizontal axis shows weeks relative to Monetary Policy Committee (MPC) surprise events, ranging from -6 weeks before the announcement to 6 weeks after. Week 0 denotes the week of the monetary policy surprise identified using the FRA1x4 instrument. The vertical axis reports the average standardized response of each search index. Source: Author's calculations using Google (2026).

Figure 1 illustrates the heterogeneous temporal responses across behavioural channels, with credit demand and informal credit searches displaying the largest post-surprise movements, while financial management and acute distress responses appear more muted and gradual.

4.2 Salience and large monetary policy surprise effects

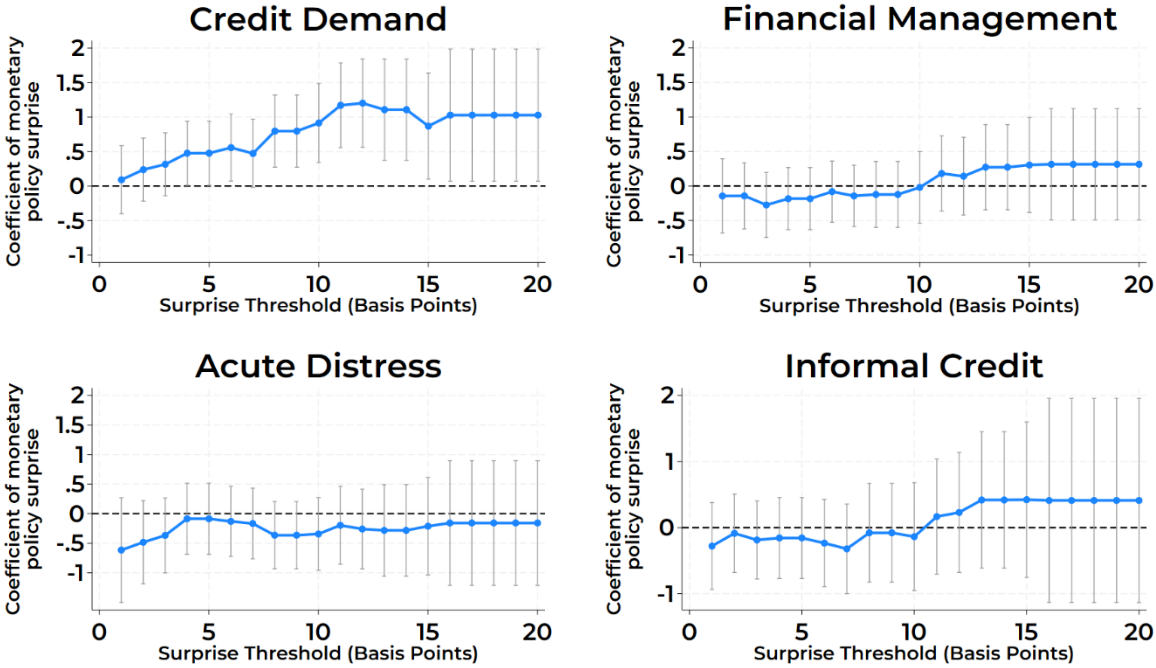
Table 3 presents the estimated behavioural responses to monetary policy surprises across alternative salience thresholds. These are presented graphically in Figure 2.

Table 3: Behavioural responses to salient monetary policy surprises

Threshold	(1) Credit Demand	(2) Financial Management	(3) Acute Distress	(4) Informal Credit
>5bp	0.476** (0.237)	-0.183 (0.230)	-0.086 (0.307)	-0.157 (0.313)
>7.5bp	0.477* (0.259)	-0.122 (0.230)	-0.143 (0.311)	-0.171 (0.355)
>10bp	0.913*** (0.292)	-0.020 (0.264)	-0.343 (0.315)	-0.137 (0.417)
>12.5bp	1.143*** (0.342)	0.129 (0.301)	-0.247 (0.359)	0.296 (0.485)
>15bp	0.868** (0.392)	0.304 (0.352)	-0.213 (0.421)	0.423 (0.601)

Note: This table reports coefficients from OLS regressions of the weekly change in search intent on a series of indicator variables $\mathbb{I}(|Surprise_t| > \gamma)$, where γ represents the specified absolute surprise threshold in basis points. Each row corresponds to a separate regression restricted to monetary policy committee (MPC) announcement weeks. Robust standard errors are reported in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, **$p < 0.01$. Sample period: 2010W1-2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Figure 2: Salience thresholds and behavioural pass-through across search channels



Note: This figure plots the estimated coefficients (β_1) and their corresponding 95% robust confidence intervals from a grid-search sensitivity analysis using the baseline specification: $\Delta\text{Search index}_t = \alpha + \beta_1 \mathbb{I}(|\text{Surprise}_t| > \gamma) + \varepsilon_t$, conditional on monetary policy committee (MPC) announcement weeks. The running threshold (γ) varies continuously along the horizontal axis from 1 to 20 basis points. The panels decompose the aggregate digital footprint into four distinct, structural behavioral channels: Credit Demand (top-left), Financial Management (top-right), Acute Distress (bottom-left), and Informal Credit (bottom-right). The horizontal dashed line marks a zero behavioral response. Confidence intervals are constructed using heteroskedasticity-robust standard errors. Sample period: 2010W1-2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

The results indicate non-linearities in household search behaviour, where the effects of surprises are amplified when background household attention is already elevated. Credit-demand searches are statistically significant and respond weakly to smaller policy surprises but increase substantially once surprises exceed approximately 10 basis points. This pattern is consistent with salience-based theories of attention, in which agents disproportionately respond to unusually large or unexpected policy signals. In contrast, searches related to acute distress and financial management show no significant responsiveness, suggesting that monetary policy surprises primarily affect forward-looking information acquisition rather than contemporaneous financial distress behaviour. Informal credit searches respond positively only at larger surprise magnitudes (11bps or more) consistent with delayed substitution toward alternative borrowing channels following sufficiently salient policy surprises.

4.3 Attention-dependent monetary transmission

Table 4 and Figure 3 examine whether the behavioural effects of monetary policy surprises depend on prevailing levels of household attention. The results provide evidence of state-dependent behavioural transmission, particularly within the credit-demand channel. The interaction coefficient between the monetary policy surprise and the lagged credit-demand index is positive and statistically significant across specifications. This indicates that the behavioural response to unexpected policy announcements becomes substantially stronger when households were already actively searching for credit-related information prior to the announcement.

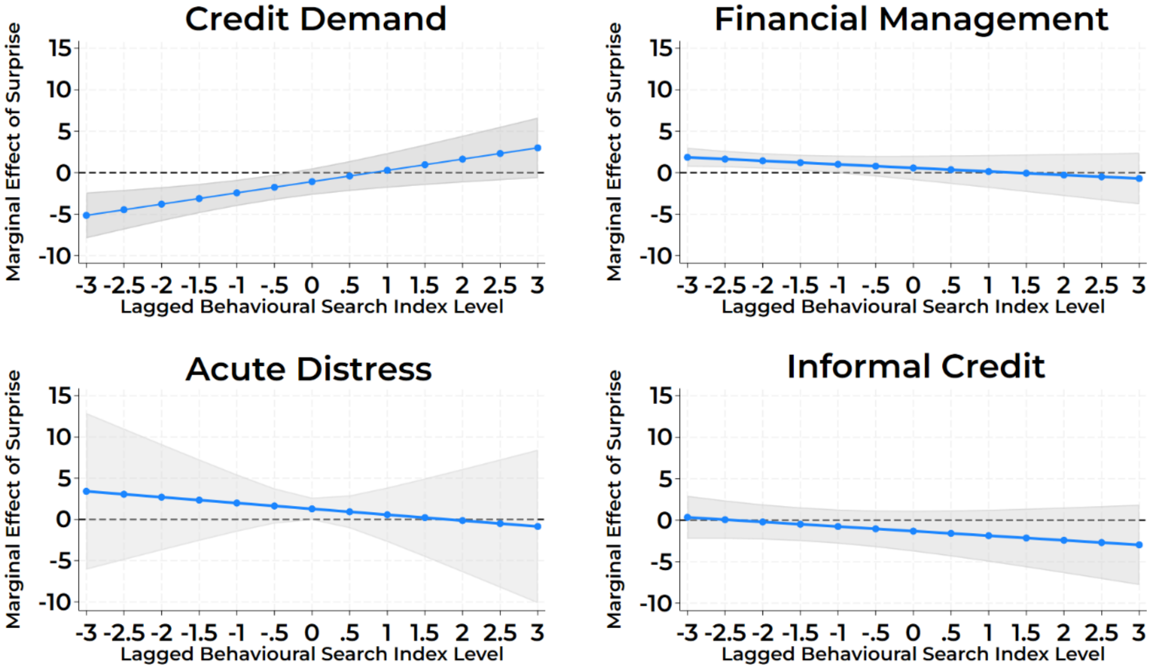
The marginal effects plots further illustrate this amplification mechanism. For the credit-demand channel, the estimated effect of a monetary policy surprise increases monotonically with the level of pre-existing household attention, suggesting that highly attentive households react disproportionately to unexpected policy information. This finding is consistent with the rational inattention models of Sims (2003) and the optimal attention allocation framework of Mackowiak and Wiederholt (2009). Capacity constraints mean people only allocate resources to search terms that yield the highest pay-off. Once households are already engaged in mortgage or credit search activity, the additional informational cost of processing a monetary policy surprise is lower, leading to a stronger behavioural response.

By contrast, the remaining behavioural channels exhibit weaker and statistically insignificant interaction effects. Financial-management and acute-distress searches display relatively flat marginal response profiles, suggesting that monetary policy surprises primarily affect forward-looking credit search behaviour rather than immediate distress-related adjustment. This asymmetry is consistent with the information-updating dynamics of Coibion, Gorodnichenko, and Weber (2022), where the public filters out complex macro communications unless the information is relevant to current economic decisions. In this context, financially constrained or distressed agents may have less scope to adjust borrowing or repayment behaviour in response to unexpected policy changes, limiting the behavioural response captured through search activity. Informal credit searches similarly exhibit limited state dependence, although the negative slope suggests that highly distressed households may already face binding financial constraints that reduce further behavioural adjustment following policy surprises.

The results are robust to the inclusion of contemporaneous changes in the USD/ZAR exchange rate and the JSE All Share Index. The stability of the coefficient estimates, statistical significance, and model fit suggests the behavioural responses are driven by monetary policy announcements rather than broader financial market fluctuations.

Overall, the results suggest that monetary policy transmission operates not only through borrowing costs and financial conditions, but also through behavioural attention mechanisms that shape how unexpected policy information is processed.

Figure 3: Attention-dependent behavioural responses to monetary policy surprises: Marginal effects



Note: Estimated marginal effect of monetary policy surprises on weekly changes in behavioural search indices conditional on pre-existing levels of household attention. Monetary policy surprises are measured using changes in the FRA1×4 contract around SARB Monetary Policy Committee announcements. The horizontal axis reports the lagged level of each behavioural search index, while the vertical axis reports the estimated marginal effect of a monetary policy surprise. Shaded regions denote 95% confidence intervals based on heteroskedasticity-robust standard errors. Panels correspond to the Credit Demand, Financial Management, Acute Distress, and Informal Credit behavioural channels. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Table 4: Attention-dependent regressions

	(1) Credit demand	(2) Credit demand	(3) Acute distress	(4) Acute distress	(5) Financial management	(6) Financial management	(7) Informal credit	(8) Informal credit
MPC surprise	-1.072	-1.038	1.279*	1.238*	0.580	0.433 (0.737)	-1.312	-1.421
	(0.799)	(0.836)	(0.680)	(0.687)	(0.736)		(1.233)	(1.253)
Lagged index	-0.283**	-0.287**	-0.776***	-0.768***	-0.730***	-0.746***	-0.925***	-0.933***
	(0.115)	(0.118)	(0.173)	(0.166)	(0.076)	(0.073)	(0.086)	(0.090)
MPC surprise × Index lagged	1.357***	1.352***	-0.711	-0.911	-0.427	-0.238	-0.553	-0.553 (502)
	(0.471)	(0.471)	(1.562)	(1.816)	(0.307)	(0.407)	(0.506)	
Constant	0.433***	0.438***	0.273	0.270*	-0.121	-0.156*	-0.545***	-0.560***
	(0.116)	(0.127)	(0.151)	(0.156)	(0.091)	(0.091)	(0.096)	(0.101)
Controls	N	Y	N	Y	N	Y	N	Y
F-stat	10.52***	6.69***	7.55**	5.07***	36.06***	25.14***	39.45***	24.61***
R^2	0.168	0.168	0.172	0.172	0.417	0.452	0.593	0.596

Note: This table reports regression estimates of the relationship between monetary policy surprises and weekly changes in behavioural search indices. Monetary policy surprises are measured using changes in the FRA1×4 contract on South African Reserve Bank (SARB) Monetary Policy Committee announcement days. The dependent variables are first differences of the behavioural search indices capturing credit demand, acute financial distress, financial management, and informal credit attention. The interaction term between monetary policy surprises and the lagged behavioural index captures whether behavioural responses depend on pre-existing household attention conditions. Control variables include contemporaneous changes in the USD/ZAR exchange rate and the JSE All Share Index. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively. Sample period: 2010W1-2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

4.4 Robustness and sensitivity

This section examines whether the baseline results remain stable across a range of alternative specifications. The analysis considers alternative surprise measures, and the exclusion of the COVID-19 period. The appendix includes further checks using disaggregated individual search terms, variations in lag structures, and potential asymmetries between positive and negative policy innovations.

4.4.1 Alternative surprise measures

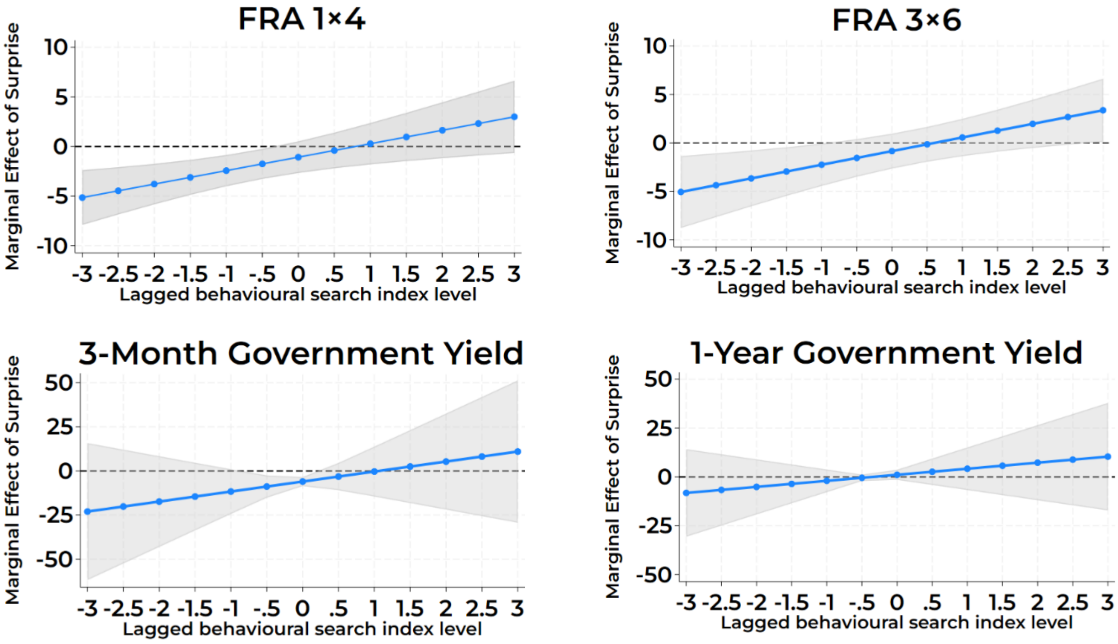
To assess identification sensitivity, Table 6 considers alternative market-based surprise measures. The interaction coefficient (between the monetary policy surprise and lagged household attention) remains positive and statistically significant when alternative FRA-based surprise measures are used. By contrast, the interaction effects for the bond-yield measures generate wider confidence intervals and weaker statistical significance. One possible explanation of this weaker precision is that it reflects how government bond yields have different informational content and absorb broader term-premium adjustments and macroeconomic shifts rather than pure policy surprises (Kuttner, 2001; Gürkaynak, Sack and Swanson, 2005). Nevertheless, the estimates in Table 6 reveal directional patterns that are consistent with the baseline results.

Table 5: Alternative monetary policy surprise measures

Policy surprise instrument	Dependent Variable: Δ Credit Demand Index			
	(1) FRA 1×4	(2) FRA 3×6	(3) 3-Month Yield	(4) 1-Year Yield
MPC surprise	-1.038 (0.836)	-0.837 (0.903)	-5.984*** (1.274)	1.103 (1.292)
Lagged index	-0.287** (0.118)	-0.287** (0.123)	-0.411*** (0.123)	-0.389*** (0.121)
MPC surprise × Index lagged	1.352*** (0.471)	1.406*** (0.502)	5.663 (6.617)	3.096 (4.184)
Constant	0.438*** (0.127)	0.446*** (0.128)	0.536*** (0.126)	0.503*** (0.131)
Controls	Y	Y	Y	Y
F-stat	6.69***	4.85***	8.28***	3.48***
R^2	0.168	0.162	0.161	0.115

Note: The dependent variable across all specifications is the weekly change in the Credit Demand Index. Monetary policy surprises are evaluated on SARB MPC announcement days using alternative proxies: (1) FRA 1×4 (baseline), (2) FRA 3×6, (3) 3-Month Government Yield, and (4) 1-Year Government Yield. Controls include contemporaneous changes in the USD/ZAR exchange rate and JSE All Share Index. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Sample period: 2010W1–2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Figure 4: Attention-dependent behavioural responses to monetary policy surprises: Marginal effects: Alternative surprise measures



Note: This figure plots the estimated marginal effect of monetary policy surprises on weekly changes in the Credit Demand index conditional on lagged household attention. The panels report estimates using alternative market-based surprise measures constructed around SARB MPC announcement days: FRA 1×4, FRA 3×6, the 3-Month Government Yield, and the 1-Year Government Yield. The 3horizontal axis reports the lagged Credit Demand index, while the vertical axis reports the estimated marginal effect of the policy surprise. Shaded regions denote 95% confidence intervals based on heteroskedasticity-robust standard errors. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

4.4.2 Excluding COVID period

To assess whether the estimated behavioural responses are driven by the exceptional macroeconomic conditions associated with the COVID-19 pandemic, the baseline specifications are re-estimated after excluding the period from 2020W11 to 2021W12. This interval captures the phase of elevated financial volatility, emergency monetary policy interventions, and unusual financial and search behaviour during the pandemic. The main interaction effects remain qualitatively similar after excluding this period, indicating that the attention-dependent behavioural transmission mechanism is not solely a product of crisis-specific dynamics.

Table 6: Behavioural responses to monetary policy surprises: excluding COVID-19 period

	(1)	(2)
Threshold	Full sample	Excluding COVID
>5bp	0.476** (0.237)	0.380 (0.233)
>7.5bp	0.477* (0.259)	0.305 (0.248)
>10bp	0.913*** (0.292)	0.661** (0.269)
>12.5bp	1.143*** (0.342)	0.821** (0.320)
>15bp	0.868** (0.392)	0.640* (0.373)

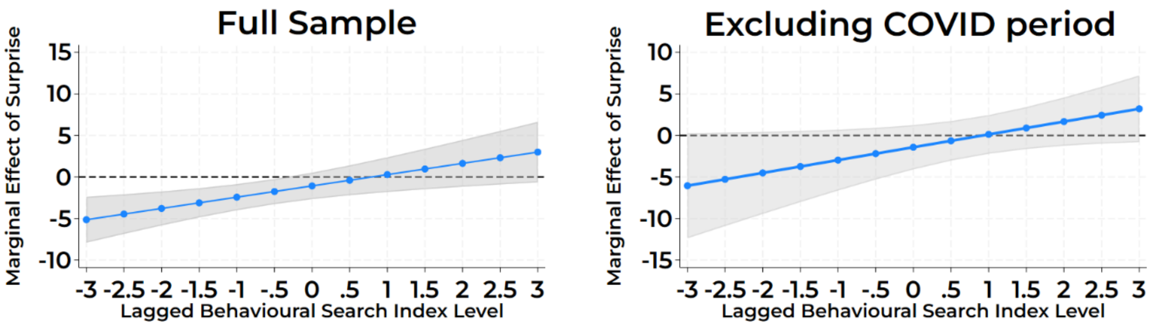
Note: This table reports estimates from salience-threshold regressions using the Credit Demand index. The "Excluding COVID" specification omits observations from 2020W11–2021W12. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Table 7: *Attention-dependent monetary transmission: excluding COVID-19 period*

	(1) Full sample	(2) Excluding COVID period
MPC surprise	-1.038 (0.836)	-1.418 (1.335)
Lagged index	-0.287** (0.118)	-0.228* (0.116)
MPC surprise × Index lagged	1.352*** (0.471)	1.544** (0.767)
Constant	0.438*** (0.127)	0.370*** (0.123)
Controls	Y	Y
F-stat	6.69***	1.95*
R^2	0.168	0.100

Note: This table reports interaction regressions for the Credit Demand index after excluding the COVID-19 period (2020W11–2021W12). Robust standard errors are reported in parentheses. Controls include changes in the USD/ZAR exchange rate and the JSE All Share Index. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Figure 5: Marginal effects of monetary policy surprises: excluding COVID-19 period



Note: This figure plots the estimated marginal effect of monetary policy surprises on the Credit Demand index conditional on lagged household attention levels after excluding the COVID-19 period (2020W11–2021W12). Shaded regions denote 95% confidence intervals. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

5. Conclusion

This paper examined whether monetary policy surprises influence financial attention and information acquisition behaviour in South Africa using high-frequency Google search data. The results show that behavioural responses to monetary policy are highly non-linear and state dependent. Small policy surprises generate little measurable response, while larger and more salient surprises trigger substantial increases in credit-related search activity. The salience-threshold results indicate that behavioural responses become economically meaningful once surprises exceed approximately 10 basis points, suggesting that households do not continuously process all policy information equally.

This study also finds that monetary policy transmission depends on pre-existing household attention conditions. Monetary policy surprises generate significantly larger behavioural responses when baseline credit-search intensity is already elevated. This finding is consistent with models of rational inattention and state-dependent salience in which households allocate attention selectively and respond more strongly when macroeconomic developments become personally relevant or financially consequential. The robustness exercises confirm that the main findings remain stable across alternative policy surprise measures and after excluding the COVID-19 period.

Overall, the findings contribute to the growing literature on rational inattention, monetary policy communication, and digital behavioural measurement by demonstrating that online search activity can capture an intermediate stage of monetary transmission before adjustments appear in conventional macroeconomic indicators. More broadly, the results suggest that the effectiveness of monetary policy transmission depends not only on the size of policy adjustments themselves, but also on whether policy announcements become sufficiently salient to trigger household information acquisition and financial attention.

Several limitations of this study warrant consideration. Google search behaviour captures revealed information demand rather than realised borrowing decisions, and search intensity may vary across demographic groups with unequal internet access. Future research could extend this framework using household-level credit data, regional heterogeneity, or alternative behavioural datasets to better understand how attention dynamics interact with realised financial adjustment and consumption behaviour.

References

1. An, P., Stedman, K.D., and Lusompa, A. 2025. How high does high frequency need to be? A comparison of daily and intra-daily monetary policy surprises. Federal Reserve Bank of Kansas City Working Paper, No. RWP 25-03. DOI: https://dx.doi.org/10.2139/ssrn.5319991
2. Aron, J., and Muellbauer, J. 2006. Estimates of household sector wealth for South Africa, 1970–2003. *Review of Income and Wealth*, 52(2): 285-307. DOI: https://doi.org/10.1111/j.1475-4991.2006.00188.x
3. Aron, J., and Muellbauer, J. 2013. Wealth, credit conditions, and consumption: Evidence from South Africa. *Review of Income and Wealth*, 59: S161-S196. DOI: https://doi.org/10.1111/roiw.12033
4. Aron, J., and Muellbauer, J. 2025. New models for South African consumption, house prices, and mortgage and non-mortgage debt. CSAE Working Paper Series, University of Oxford. [Online]. Available: https://www.csae.ox.ac.uk/publication/2309145/ora-hyrax
5. Askitas, N., and Zimmermann, K.F. 2009. Google econometrics and unemployment forecasting. *Applied Economics Quarterly,* 55(2): 107-120. DOI: https://doi.org/10.3790/aeq.55.2.107
6. Beltrán, F. 2025. Global monetary policy surprises and their transmission to emerging market economies: An external VAR analysis. *Emerging Markets Review,* 68: 101333. DOI: https://doi.org/10.1016/j.ememar.2025.101333
7. Bernanke, B.S. and Gertler, M. 1995. Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives,* 9(4): 27-48. DOI: https://doi.org/10.1257/jep.9.4.27
8. Bernanke, B.S., and Kuttner, K.N. 2005. What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance,* 60(3): 1221-1257. DOI: https://doi.org/10.1111/j.1540-6261.2005.00760.x

9. Bernanke, B.S., Boivin, J., and Eliasz, P. 2005 Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach, *The Quarterly Journal of Economics*, 120(1): 387-422 DOI: https://doi.org/10.1162/0033553053327452
10. Bordalo, P., Gennaioli, N., and Shleifer, A. 2012. Salience Theory of Choice Under Risk, *The Quarterly Journal of Economics*, 127(3): 1243-1285. DOI: https://doi.org/10.1093/qje/qjs018
11. Bracha, A., and Tang, J. 2025. Inflation levels and (in)attention. *The Review of Economic Studies,* 92(3): 1564-1594. DOI: https://doi.org/10.1093/restud/rdae063
12. Bulut, L. 2017. Google Trends and the forecasting performance of exchange rate models. *Journal of Forecasting,* 37(3): 303-315. DOI: https://doi.org/10.1002/for.2500
13. Checo, A., Grigoli, F. and Sandri, D., 2024. *Monetary policy transmission in emerging markets: proverbial concerns, novel evidence*. IMF Working Papers, 2024/093. DOI: https://doi.org/10.5089/9798400268564.001
14. Choi, H., and Varian, H. 2012. Predicting the present with Google Trends. *Economic Record,* 88(1): 2-9. DOI: https://doi.org/10.1111/j.1475-4932.2012.00809.x
15. Coibion, O., Gorodnichenko, Y. and Weber, M., 2022. Monetary policy communications and their effects on household inflation expectations. *Journal of Political Economy*, 130(6): 1537-1584. DOI: https://doi.org/10.1086/718982
16. Cook, T., and Hahn, T. 1989. The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics,* 24(3): 331-351. DOI: https://doi.org/10.1016/0304-3932(89)90025-1
17. D'Amuri, D., and Marcucci, J. 2017. The predictive power of Google searches in forecasting US unemployment. *International Journal of Forecasting,* 33(4): 801-816. DOI: https://doi.org/10.1016/j.ijforecast.2017.03.004
18. Da, Z., Engelberg, J. and Gao, P., 2011. In search of attention. *Journal of Finance*, 66(5), pp.1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x
19. Damianov, D.S., Wang, X., and Yan, C. 2021. Google search queries, foreclosures, ad house prices. *Journal of Real Estate Finance and Economics,* 63: 177-209. DOI: https://doi.org/10.1007/s11146-020-09789-y
20. de Villiers, D.J. 2026. Digital search behaviour and the housing credit cycle: Evidence from South Africa. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6534578
21. Donadelli, M. 2015. Google search-based metrics, policy-related uncertainty and macroeconomic conditions. *Applied Economics Letters,* 22(10): 801-807. DOI: https://doi.org/10.1080/13504851.2014.978070
22. Friedman, M. 1961. The lag in effect of monetary policy, *Journal of Political Economy,* 69(5): 447-447. DOI: https://doi.org/10.1086/258537
23. Gabaix, X. 2020. A behavioural new Keynesian Model. *American Economic Review,* 110(8): 2271-2327. DOI: https://doi.org/10.1257/aer.20162005
24. Gertler, M. and Karadi, P. 2015. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics,* 7(1): 44-76. DOI: https://doi.org/10.1257/mac.20130329
25. Google. 2026. *Google Trends*. [Online]. Available: https://trends.google.com/ [Accessed 2026 /05/15].
26. Gürkaynak, R.S., Hakan Kara, A., Kısacıkoğlu, B. Lee, S.S. 2021. Monetary policy surprises and exchange rate behaviour. *Journal of International Economics,* 130: 103443. https://doi.org/10.1016/j.jinteco.2021.103443
27. Gürkaynak, R.S., Sack, B., and Swanson, E. 2005. Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central banking,* 1(1): 55-93. URL: https://www.ijcb.org/sites/default/files/journal/v1n1/ijcb-v1n1-do-actions-speak-louder-words-response-asset-prices-monetary-policy-actions-and-statements.pdf

28. Ho, S.-J. and Karagedikli, Ö. 2025. Effects of monetary policy communication in emerging market economies: evidence from Malaysia, *Journal of International Money and Finance*, 158: 103379. DOI: https://doi.org/10.1016/j.jimonfin.2025.103379
29. International Monetary Fund (IMF). 2024. *World Economic Outlook – Steady but slow: Resilience amid divergence.* [Online]. Available: https://www.imf.org/-/media/files/publications/weo/2024/april/english/text.pdf
30. International Monetary Fund. 2026. South Africa: 2025 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for South Africa. *IMF Staff Country Reports*, 034: A001. DOI: https://doi.org/10.5089/9798229037372.002.A001
31. Jarociński, M., and Karadi, P. 2020. Deconstructing monetary policy surprises – The role of information shocks. *American Economic Journal: Macroeconomics*, 12(2): 1-43. DOI: https://doi.org/10.1257/mac.20180090
32. Jarociński, M., and Karadi, P. 2020. Deconstructing monetary policy surprises – The role of information shocks. *American Economic Journal: Macroeconomics*, 12(2): 1-43. DOI: https://doi.org/10.1257/mac.20180090
33. Jo, S., Shim, M., and Varghese, A. 2026. Attention to Monetary Policy. SSRN Electronic Journal. [Online]. Available: https://doi.org/10.2139/ssrn.6398378
34. Jo, S., Shim, M., and Varghese, A. 2026. Attention to monetary policy. SSRN Working paper. DOI: http://dx.doi.org/10.2139/ssrn.6398378
35. Juselius, M., and Xia, D. 2026. Monetary responses to external shocks in emerging market economies: The role of financial vulnerabilities. *BIS Quarterly Review.* [Online]. Available: https://www.bis.org/publ/qtrpdf/r_qt2603e.pdf
36. Krige, D. 2019. Debt/credit, money and social relationships in the underground credit markets of Soweto, South Africa. *Social Science Information,* 58(3): 403-429. DOI: https://doi.org/10.1177/0539018419851767
37. Kuttner, K.N., 2001. Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics,* 47(3): 523-544. DOI: https://doi.org/10.1016/S0304-3932(01)00055-1
38. Lakdawala, A. and Sengupta, R. 2024 Measuring monetary policy shocks in emerging economies: evidence from India, *Journal of Money, Credit and Banking*. DOI: https://doi.org/10.1111/jmcb.13144.
39. London Stock Exchange Group (LSEG). 2026. *Datastream.* Available at: https://www.lseg.com/ [Accessed 2026/05/15].
40. Lu, D., Tang, H. and Zhang, C. 2023 China's monetary policy surprises and corporate real investment, *China Economic Review*, 77:101893. DOI: https://doi.org/10.1016/j.chieco.2022.101893.
41. Macauley, A. 2025. Cyclical Attention to Saving. *American Economic Journal: Macroeconomics,* 17(4): 124-167. DOI: https://doi.org/10.1257/mac.20220311
42. Mackowiak, B., and Wiederholt, M. 2009. Optima sticky prices under rational inattention. *American Economic Review,* 99(3): 769-803. DOI: https://doi.org/10.1257/aer.99.3.769
43. Meurer, R., Santos, A.A.P. and Turatti, D.E. 2015. Monetary policy surprises and jumps in interest rates: evidence from Brazil, *Journal of Economic Studies*, 42(5): 893–907. DOI: https://doi.org/10.1108/JES-07-2014-0113.
44. Mian, A., and Sufi, A. 2018. Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives*, = 32(3): 31-58. DOI: https://doi.org/10.1257/jep.32.3.31
45. Mishkin, F.S. 1996. The channels of monetary transmission: Lessons for monetary policy. NBER Working paper 5464. DOI: https://doi.org/10.33866/w5464
46. Mishkin, F.S., 1996. The channels of monetary transmission: Lessons for monetary policy. National Bureau of Economic Research (NBER), Working paper 5464. DOI: https://doi.org/10. 3386/w5464

47. Møller, S.V., Pedersen, T. Schütte, E.C.M, and Timmermann, A. 2023. Search and predictability of prices in the housing market. *Management Science,* 70(1): 1-670. DOI: https://doi.org/10. 1287/ mnsc.2023.4672
48. Nakamura, E., and Steinsson, J. 2018. High-Frequency Identification of Monetary Non-Neutrality: The Information Effect, *The Quarterly Journal of Economics*, 133(3): 1283-1330. DOI: https://doi.org/10.1093/qje/qjy004
49. Pfäuti, O. 2026. The inflation attention threshold and inflation surges. Working paper. [Online]. Available: https://www.oliverpfaeuti.com/website/IAT.pdf
50. Pirozhkova, E., Ricco, G., and Viegi, N. 2024. Trouble every day: Monetary policy in an open emerging economy. ERSA Working Paper Series, 891. DOI: https://doi.org/10.71587/x1sx7n51
51. Preis, T., Moat, H. and Stanley, H. 2013. Quantifying trading behavior in financial markets using *Google Trends*. *Scientific Reports,* 3(1684). DOI: https://doi.org/10.1038/srep01684
52. Reid, M. 2009. The sensitivity of South African inflation expectations to surprises. *South African Journal of Economics*, 77: 414-429. DOI: https://doi.org/10.1111/j.1813-6982.2009.01219.x
53. Reid, M. and Du Plessis, S. 2010. Loud and clear? Can we hear when the SARB speaks?. *South African Journal of Economics,* 78: 269-286. DOI: https://doi.org/10.1111/j.1813-6982.2010. 01246.x
54. Reis, R. Inattentive consumers. *Journal of Monetary Economics,* 53(8): 1761-1800. DOI: https://doi.org/10.1016/j.jmoneco.2006.03.001
55. Sims, C. 2003. Implications of rational inattention. *Journal of Monetary Economics,* 50(3): 665-690. DOI: https://doi.org/10.1016/S0304-3932(03)00029-1
56. South African Reserve Bank (SARB). 2026. *Monetary Policy Committee Statements*. [Online]. Available: https://www.resbank.co.za/en/home/publications/statements/mpc-statements [Accessed 2026/05/11].
57. Stiglitz, J.E., and Weiss, A. 1981. Credit rationing in markets with imperfect information. *The American Economic Review,* 71(3): 393-410. URL: https://www.jstor.org/stable/1802787
58. Stolbov, M., and Shchepeleva, M. 2025. A sentiment-based financial stress index for Russia. *Borsa Istanbul Review,* 25(2): 350-359. DOI: https://doi.org/10.1016/j.bir.2025.01.007
59. Stolbov, M., Shchepeleva, M., and Karminsky, A. 2022. When central bank research meets Google search: A sentiment index of global financial stress. *Journal of International Financial Markets, Institutions and Money,* 81: 101692. DOI: https://doi.org/10.1016/j.intfin.2022.101692
60. Woloszko, N., 2024. Nowcasting with panels and alternative data: The OECD weekly tracker. *International Journal of Forecasting,* 40(4): 1302-1335. DOI: https://doi.org/10.1016/j.ijforecast. 2023.11.005
61. Wu, L., and Brynjolfsson, E. The future of prediction: How Google searches foreshadow housing prices and quantities. *ICIS 2009 Proceedings,* 147. URL: http://aisel.aisnet.org/icis2009/147.

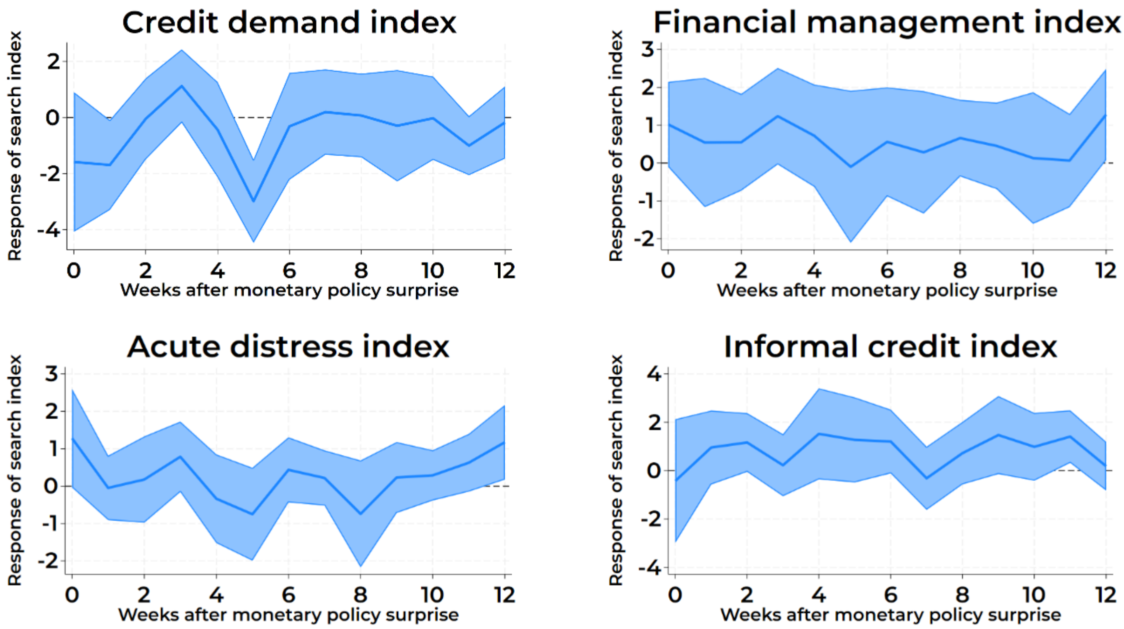
Appendix

Table A1: Search terms by dimension, and factor loadings

Dimension	Search terms		
		Factor loadings	Dimension summary
Credit demand	bond calculator	0.6729	PC1 Var: 41.3%
	home loan	0.6805	Cronbach: 0.42
	credit score	0.2873	
	Preapproval	-0.0406	
Financial management	debt review	0.6628	PC1 Var: 50.0%
	debt consolidation	0.6409	Cronbach: 0.48
	debt help	0.3871	
Acute distress	Garnishee	0.7071	PC1 Var: 53.0%
	missed payment	0.7071	Cronbach: 0.11
Informal credit	loan shark	0.3973	PC1 Var: 39.0%
	Mashonisa	0.5095	Cronbach: 0.47
	payday loan	0.4588	
	cash loan	0.6099	

Notes: Factor loadings represent the statistical weight of each term within its specific sub-dimension. Data is sourced from Google Trends (2010–2026).

Figure A1: Impulse responses of behavioural search channels to monetary policy surprise



This figure reports local projection impulse responses of behavioural search channels to high-frequency monetary policy surprises identified using changes in the FRA1x4 contract around South African Monetary Policy Committee announcements. Solid lines denote estimated responses across weekly horizons, while shaded regions represent 95% Newey–West confidence intervals.

Contractionary monetary policy surprises generate the strongest immediate responses within the Credit Demand index, indicating a rapid decline in forward-looking borrowing and mortgage-related search activity. By contrast, financial distress and informal credit searches exhibit weaker but more persistent, delayed responses, suggesting that behavioural adjustment occurs gradually through debt-management and alternative credit channels.

Further robustness and sensitivity
Disaggregated behavioural responses

Table A2 reports the interaction specification estimated separately for the individual search terms that make up each behavioural index. The aim of this exercise is to determine whether the baseline findings reflect a broader behavioural pattern or are driven by a small number of specific search terms.

The strongest and most consistent amplification effects emerge within the forward-looking credit-search category (columns 1-4). In particular, the interaction term remains positive and statistically significant for “bond calculator”, indicating that monetary policy surprises generate larger behavioural responses when people are already actively searching for mortgage-related information. In contrast, search terms associated with financial distress or debt management show weaker and less systematic consistent effects.

The results therefore suggest that the baseline state-dependent mechanism mainly reflects anticipatory credit-search behaviour rather than contemporaneous financial stress adjustment.

This pattern supports the interpretation that people respond more strongly to unexpected monetary policy announcements when they are already engaged in economically actionable search activity related to borrowing and housing decisions. This finding is consistent with rational inattention frameworks in which attention is allocated towards information that is most relevant to current decision-making (Sims, 2003; Mackowiak and Wiederholt, 2009).

Table A2: Attention-dependent responses across individual search terms

	(1) Bond calculator	(2) Home loan	(3) Preapproval	(4) Credit score	(5) Debt review	(6) Debt consolidation	(7) Debt help	(8) Garnishee	(9) Missed payment	(10) Loan shark	(11) Mashonisa	(12) Payday loan	(13) Cash loan
MPC surprise	-0.348	-1.003	0.296	0.102	0.120	0.647	-0.091	0.951*	0.315	-0.449	-1.869	-0.636	-0.164
	(1.058)	(0.883)	(0.386)	(0.644)	(0.540)	(0.562)	(0.690)	(0.563)	(0.593)	(0.668)	(2.372)	(0.628)	(0.565)
Lagged search term	-0.544***	-0.516***	-3.907	-0.635***	-0.830***	-0.724***	-1.038***	-0.793***	-0.939***	-0.884***	-0.945***	-0.918***	-0.895***
	(0.112)	(0.107)	(3.389)	(0.109)	(0.075)	(0.094)	(0.104)	(0.114)	(0.263)	(0.075)	(0.110)	(0.094)	(0.122)
MPC surprise × lagged search term	1.266*	0.655	-10.712	-0.436	-0.604	0.093	0.375	0.551	-9.284*	-1.229	-1.218	0.272	-0.106
	(0.672)	(0.588)	(55.805)	(0.426)	(0.374)	(0.574)	(0.941)	(1.050)	(4.883)	(0.976)	(1.752)	(0.522)	(0.333)
Constant	0.465***	0.290***	0.068	0.037	-0.075	-0.186**	0.034	0.113	0.214	-0.204**	-0.037	-0.264***	-0.515***
	(0.113)	(0.099)	(0.090)	(0.098)	(0.083)	(0.081)	(0.098)	(0.101)	(0.176)	(0.087)	(0.119)	(0.094)	(0.083)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat	9.37***	6.70***	0.41	8.70***	30.79***	15.41***	20.48***	18.88***	3.49***	41.79***	18.35***	20.94***	26.13***
R^2	0.232	0.219	0.069	0.350	0.516	0.453	0.455	0.441	0.069	0.653	0.371	0.591	0.635

Note: This table reports regression estimates of the relationship between monetary policy surprises and weekly changes in individual Google search terms related to household credit behaviour. Monetary policy surprises are measured using changes in the FRA1×4 contract on South African Reserve Bank (SARB) Monetary Policy Committee announcement days. The dependent variables are first differences of the standardised individual search terms. The interaction term between the monetary policy surprise and the lagged search term captures whether behavioural responses depend on pre-existing search intensity. Control variables include contemporaneous changes in the USD/ZAR exchange rate and the JSE All Share Index. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively. Sample period: 2010W1-2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Alternative lag structure

Table A3 and Figure A2 examine whether the attention-dependent behavioural response is sensitive to alternative lag structures. The interaction coefficient remains positive and statistically significant when using a two-week lag and a three-week rolling average of the Credit Demand index, suggesting that the amplification mechanism is not driven by short-term measurement noise.

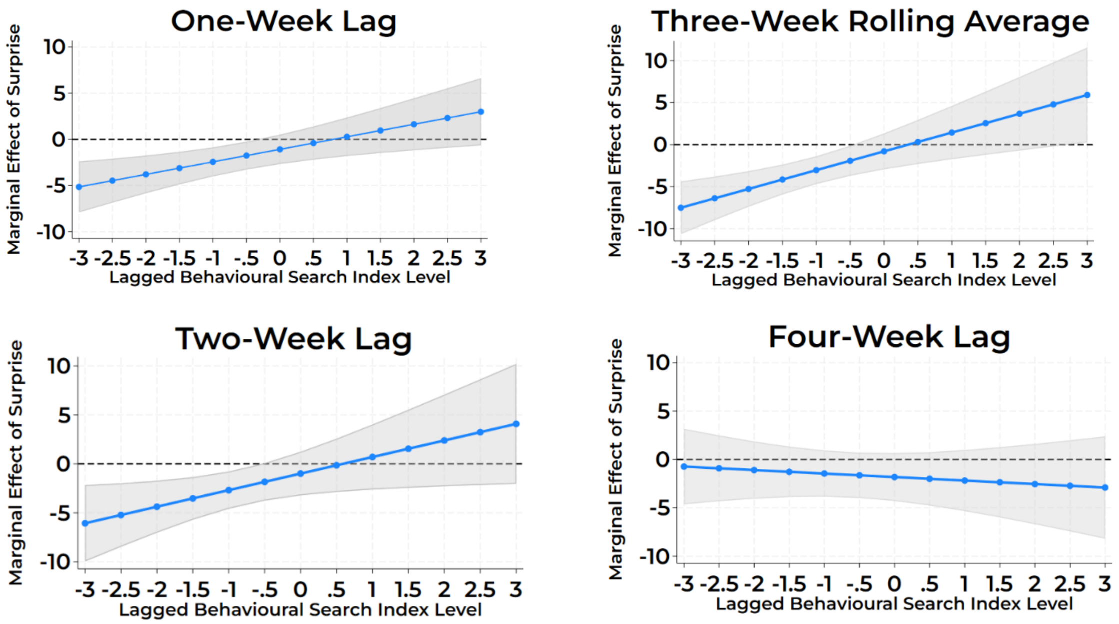
By contrast, the interaction effect becomes statistically insignificant at longer horizons, indicating that the behavioural attention state is relatively short-lived. This pattern is consistent with models of limited attention in which household responsiveness to macroeconomic information depends on recent engagement with credit-related information acquisition (Sims, 2003; Reis, 2006).

Table A3: Alternative Lag structures

	(1) Baseline: One-Week Lag	(2) Two-Week Lag	(3) Four-Week Lag	(4) Three-Week Rolling Average
MPC surprise	-1.038 (0.836)	-0.995 (1.119)	-1.812 (1.243)	-0.800 (1.074)
Lagged index	-0.287** (0.118)	0.055 (0.133)	-0.032 (0.072)	0.012 (0.159)
MPC surprise × Index lagged	1.352*** (0.471)	1.693** (0.777)	-0.361 (0.660)	2.236*** (0.676)
Constant	0.438*** (0.127)	0356*** (0.130)	0.371*** (0.131)	0.350*** (0.129)
Controls	Y	Y	Y	Y
F-stat	6.69***	2.31*	0.52	6.52***
R^2	0.168	0.080	0.046	0.103

Note: This table reports interaction regressions using alternative lag structures for the Credit Demand index. Specifications include a two-week lag, a four-week lag, and a three-week rolling average. Robust standard errors are reported in parentheses. Controls include changes in the USD/ZAR exchange rate and the JSE All Share Index. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Figure A2: Attention-dependent behavioural responses to monetary policy surprises: Marginal effects



Note: This figure plots the estimated marginal effect of monetary policy surprises on the Credit Demand index conditional on alternative lag specifications of household attention. Shaded regions denote 95% confidence intervals. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Positive vs negative surprises

Table A4 evaluates whether behavioural responses differ across positive and negative monetary policy surprises (using 10 basis point threshold). Both positive and negative surprises lead to statistically significant increases in credit-demand searches, suggesting that people's attention responds when policy announcements deviate from expectations. The estimated effect is larger for positive surprises; this is consistent with the idea that unexpected monetary tightening shocks generate greater urgency in credit-related information acquisition when borrowing costs increase unexpectedly (Bordalo, Gennaioli and Shleifer, 2012). In other words, positive surprises may be more salient because they immediately worsen borrowing affordability. Overall, the results support the notion that the salience of policy announcements depends mainly on how unexpected they are, rather than whether rates move up or down.

Table A4: Asymmetric behavioural responses to large monetary policy surprises

	(1) Baseline	(2) Positive surprises	(3) Negative surprise	(4) Joint specification
Large surprise (>10bp)	0.913*** (0.292)			
Positive surprise (>10bp)		0.939** (0.418)		1.068** (0.421)
Negative surprise (<-10bp)			0.723* (0.366)	0.824** (0.368)
Constant	0.197 (0.126)	0.325** (0.123)	0.299** (0.125)	0.197 (0.126)
F-stat	9.75***	5.03**	3.91*	5.19***
R^2	0.104	0.047	0.046	0.106

Note: This table reports OLS estimates of the behavioural response of the Credit Demand index to large monetary policy surprises identified using changes in the FRA 1×4 contract around SARB MPC announcement days. Large surprises are defined as announcement-week surprises exceeding an absolute threshold of 10 basis points. Columns (2) and (3) separately estimate the effects of positive and negative surprises. Column (4) jointly estimates positive and negative surprise indicators to assess asymmetric behavioural responses. The dependent variable is the weekly change in the Credit Demand index. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Sample period: 2010W1–2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Table A5 extends the analysis by estimating the interaction specification separately for positive and negative monetary policy surprises. Figure A3 plots the corresponding marginal effects of the different surprises, conditional on pre-existing household attention. Although the interaction coefficients lose statistical significance once the sample is divided by shock direction, the estimated patterns remain informative.

Positive surprises display a modest upward-sloping marginal effect, suggesting stronger amplification when baseline attention is already elevated. By contrast, negative surprises produce a flatter and slightly downward-sloping profile, indicating weaker amplification following unexpected easing episodes. The wider confidence intervals are indicative of the limited number of large directional surprise events.

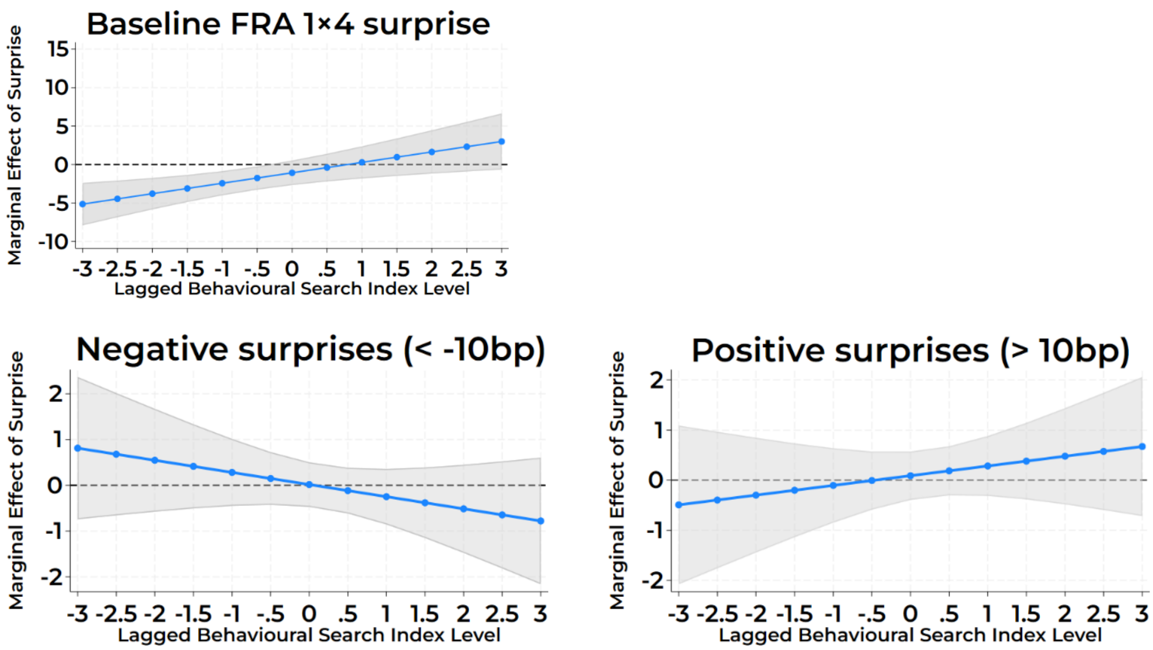
Overall, the results suggest that the baseline state-dependent mechanism is present under both surprises that tighten or ease, although the amplification appears somewhat stronger following unexpected policy tightening surprises.

Table A5: Asymmetric state-dependent behavioural responses to monetary policy surprises

	(1) Baseline FRA 1×4	(2) Positive surprises (> 10bp)	(3) Negative surprises (< -10bp)
MPC surprise	-1.038 (0.836)	0.090 (0.243)	0.016 (0.245)
Lagged index	-0.287** (0.118)	-0.476*** (0.175)	-0.243 (0.149)
MPC surprise × Index lagged	1.352*** (0.471)	0.194 (0.236)	-0.265 (0.233)
Constant	0.438*** (0.127)	0.448*** (0.164)	0.481** (0.187)
Controls	Y	Y	Y
F-stat	6.69***	2.30*	2.33**
R^2	0.168	0.119	0.122

Note: This table reports interaction regressions for Credit Demand using changes in the FRA 1×4 surprises. Columns (2) and (3) isolate positive (>10 bps) and negative (<-10 bps) shocks. . Control variables include lagged changes in the USD/ZAR exchange rate and the JSE All Share Index. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Sample period: 2010W1–2026W19. 98 observations. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).

Figure A3: Marginal effects of positive and negative monetary policy surprises



Note: This figure plots the estimated marginal effect of FRA 1×4 surprises on Credit Demand across lagged attention states. The horizontal axis reports the lagged level of the Credit Demand index, while the vertical axis reports the estimated marginal effect of the policy surprise. Shaded regions denote 95% confidence intervals constructed using heteroskedasticity-robust standard errors. Source: Author's calculations using SARB (2026), LSEG (2026) and Google (2026).