

Behavioural early warning indicators of household sector vulnerability

David de Villiers

ERSA working paper 945

November 2026

The views expressed are those of the author(s) and do not necessarily represent those of the funder, ERSA or the author's affiliated institution(s). ERSA shall not be liable to any person for inaccurate information or opinions contained herein.

Behavioural early warning indicators of household sector vulnerability

David de Villiers[1]

Abstract

Conventional indicators of household financial vulnerability are published with substantial lags. This paper examines whether Google search behaviour can provide earlier signals in South Africa. Three behavioural early warning indicators are constructed from Google Trends data, capturing housing and mortgage demand, formal financial distress and informal credit substitution (mashonisa loans). Their predictive performance is evaluated using quasi-real-time recursive out-of-sample forecasts from January 2015 for seven banking, credit and housing outcomes at horizons of up to 24 months. Used individually, the indices achieve higher AUROCs than the credit-to-GDP gap and monthly macro indicators in six of the seven outcomes, with the clearest signals one to eight months ahead. The signal is statistically clear for household credit busts (Demand and Distress), deposit collapses (the informal-credit Shadow index) and house price booms (Distress), and lasts roughly 8 to 13 months. The indices also provide statistically significant incremental predictive information beyond established macro-financial indicators such as the credit-to-GDP gap, notably for household credit busts. The gains over the gap are robust to alternative event definitions, estimation choices and information timing, and disappear when the indices are shifted in time. Search behaviour therefore complements, rather than replaces, macro-financial data, and offers central banks a timely, low-cost addition to early warning systems, potentially helping them monitor household financial vulnerability where informal credit is hard to measure.

Keywords: Macroprudential surveillance; Early warning systems; Digital search data; Household vulnerability; Informal credit; South Africa

JEL codes: C53; G21; G28; E44

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

1 Introduction

Macroprudential policy aims to safeguard financial stability by limiting the build-up of systemic risk (Borio, 2003; Hanson, Kashyap and Stein, 2011). To support timely policy intervention, central banks increasingly rely on early warning systems (EWS) that monitor macro-financial indicators including housing, credit to identify the emergence of financial vulnerabilities before they threaten the stability of the financial system (Ferrari et al., 2015; Dierick et al., 2016; Hagemann and Wohlmann, 2019).[2] However, these indicators are constructed almost exclusively from indicators that measure realised economic outcomes – published at low frequencies, with delays (Kawata, Kurachi, Nakamura, and Teranishi, 2013)[3], and often undergo statistical revisions (Edge and Meisenzahl, 2011; Alessandri, Bologna, and Galardo, 2022). As a result, they provide limited information about the behavioural processes through which housing market vulnerabilities begin to emerge, potentially delaying the identification of turning points in housing and mortgage credit cycles.

Housing markets play a central role in the build-up of macroprudential vulnerabilities because household borrowing, credit conditions and housing demand reinforce one another over the financial cycle (Claessens et al., 2012; Mian and Sufi, 2018). Household financial decision-making begins well before a mortgage is approved or a property transaction is recorded. Prospective buyers typically engage in a period of information acquisition during which they search for properties, financing options, affordability constraints and borrowing requirements. This behaviour reflects evolving expectations and perceived financial constraints, generating observable behavioural signals before credit is extended or transactions are completed (Case and Shiller, 2003; Kaplan, Mitman and Violante, 2020). We call these signals behavioural because they record actions households take, such as looking for a property, a loan or debt relief, as opposed to balance-sheet and price statistics compiled by banks and statistical agencies, or surveys of what households say.

The increasing availability of digital search data has created an empirical opportunity to observe latent behavioural processes in real time, bypassing the structural reporting lags and revision bottlenecks inherent in official administrative statistics. Google Trends provides high-frequency measures of aggregate information acquisition that provide an early observable

[2] Existing surveillance frameworks typically rely on indicators representing the housing market (house prices, house price growth, price-to-income ratio, price-to-rent ratio, residential investment, construction); credit (household credit growth, credit-to-GDP gap, mortgage lending, debt service ratio, lending standards); macro (interest rates, money market rate, GDP growth, inflation, money supply, exchange rates) (Ferrari et al, 2015; Dierick et al., 2016; Hagemann and Wohlmann, 2019).

[3] These measurement challenges mirror the real-time unreliability of output gap estimates (see Orphanides and van Norden, 2002). For an early discussion of how policy efficacy degrades under recognition and implementation lags, see Friedman (1948).

indication of changes in housing demand and household risk appetite. Search data has been used to nowcast economic indicators, such as output, unemployment and consumer behaviour (Choi and Varian, 2012; Woloszko, 2024). Notably, Preis, Moat and Stanley (2013) show that changes in finance-related Google search intensity precede stock market movements. Within housing markets, previous studies show that search activity predicts house prices (Wu and Brynjolfsson, 2009), transaction volumes (Dietzel, 2016) and market turning points (Bulczak, 2021), while others interpret search intensity as a proxy for housing demand, market attention and speculative activity (Beracha and Wintoki, 2013; Bełej, 2023). Despite the documented usefulness of search behaviour in capturing market shifts before conventional macroeconomic indicators, and the need for EWS to detect emerging imbalances before they materialise, there is limited evidence as to whether search-based indicators can improve early warning models across housing, credit and banking cycles, particularly in emerging market economies. The closest papers are Stolbov et al. (2022) and Stolbov and Shchepeleva (2025), who construct search-based indicators of financial stress that anticipate conventional stress measures, and the housing studies above, which predict house prices and transactions. Our contribution is to test search indices against the credit-to-GDP gap and macro-financial controls, for household credit, deposit and housing events.

The formalisation of EWSs provides macroprudential authorities with a systematic approach to identify systemic imbalances and guide timely regulatory interventions (Kaminsky, Lizondo and Reinhart, 1998; Alessi and Detken, 2011; Lo Duca and Peltonen, 2013). Rather than viewing indicators in isolation, contemporary EWS frameworks aggregate information from a broad spectrum of macro-financial metrics – spanning private credit, asset prices, monetary conditions, and the real economy – to actively assess the joint likelihood of future financial distress (Ferrari et al., 2015). The credit-to-GDP gap consistently demonstrates strong predictive performance for systemic banking crises (Drehmann and Juselius, 2014). More recent studies have expanded these frameworks by demonstrating that household debt, cross-border borrowing and property prices contain additional predictive information for systemic banking crises (Aldasoro, Borio and Drehmann, 2018), while others have explored nonlinear and machine-learning approaches to improve forecasting performance (Kwon and Park, 2023). Similarly, in South Africa, the EWS literature has focused on refining conventional regulatory indicators (Burra et al., 2015; Msiska et al., 2026).[4]

[4] Burra et al. (2015) evaluate alternative indicators for calibrating the Basel III Countercyclical Capital Buffer, while Msiska, Sikhosana and Vermeulen (2026) show that the credit-to-GDP gap provides a reliable real-time measure of emerging financial imbalances.

This paper extends this literature by developing Behavioural Early Warning Indicators (BEWIs) to enhance macroprudential surveillance. To do this, it constructs three theory-driven indicators of distinct behavioural transmission channels: housing demand – reflecting formal housing and mortgage demand; formal financial distress – tracking consumer engagement with formal safety nets and debt restructuring mechanisms; and informal credit substitution – proxying shifts towards shadow-market borrowing. These indicators are then evaluated in quasi-real-time recursive out-of-sample forecasts starting in January 2015, for seven banking, credit and housing outcomes at horizons of up to 24 months. The evaluation asks whether the indicators carry predictive information on their own and whether they add to conventional macro-financial indicators.

This paper asks whether high-frequency digital search activity can bridge this surveillance gap by capturing pre-transactional behaviour and shadow market dynamics before they materialise in official statistics. Macroeconomic forecasting asks how well search data predict the level or growth of a variable such as output or unemployment. Macroprudential surveillance asks whether an indicator flags, months ahead, that a rare boom or bust is about to begin, and whether it does so better than benchmarks already in use. We therefore evaluate event probabilities with AUROC against surveillance benchmarks, not point-forecast errors. The paper makes three main contributions. First, it extends the literature on digital search data to macroprudential surveillance, using quasi-real-time forecasts that respect publication lags. Second, it contributes to the financial stability literature by demonstrating that behavioural search indicators provide statistically significant incremental predictive information beyond established macro-financial indicators such as the credit gap. Moreover, the channels differ: housing demand and formal financial distress lead household credit busts, informal credit substitution leads deposit collapses, and formal financial distress leads house price booms. Third, it provides evidence on the value of high-frequency behavioural indicators in an emerging market setting – where official financial statistics are subject to reporting lags (which are often longer) and shadow financial activity is otherwise unobservable through standard supervisory channels.

2 Data and methodology

To assess whether behavioural indicators provide incremental predictive power for household sector vulnerability, we employ a discrete-choice early warning system (EWS) framework. Consistent with the macroprudential literature, EWS performance is increasingly evaluated not only by standard in-sample statistical significance, but also by the model's ability to correctly classify crises and turning points across alternative forecast horizons h and varying decision

thresholds. We therefore evaluate every model out of sample: models are re-estimated each month on the information available at that date, the first forecast is for January 2015, and the forecasts from August 2023 onwards are held back and evaluated once. Following Borio and Drehmann (2009) and Alessi and Detken (2011), we model the probability of a household-sector vulnerability event occurring within a forward-looking horizon $h \in \{3, 6, 12, 24\}$ months. The sample runs from January 2010 to December 2025.

2.1 Econometric specification

Let $y_t \in \{0,1\}$ be a binary indicator equal to one if an episode of a specific macroprudential turning point (a sustained boom or bust in one of the outcomes defined under Dependent variables) starts in month t. In an early warning framework designed for policy action, predicting the exact month of a crisis is less useful than identifying a vulnerable state that precedes the event.

Therefore, following Alessi and Detken (2011), we define our dependent variable as a forward-looking "pre-crisis" window:

$$Y_{t,h} = \max_{j \in [1,h]} \{y_{t+j}\}$$

where $Y_{t,h} = 1$ if an episode starts at any point in months t+1, …, t+h, and 0 otherwise. A window that runs beyond the last observed month and contains no observed episode start is set to missing rather than to zero, because the unobserved months could still contain one. This forward-looking specification enables the models to identify periods of elevated vulnerability sufficiently in advance to support timely macroprudential intervention.

Event definition

For each outcome a month is in breach when the outcome lies above its 90th percentile (boom) or below its 10th percentile (bust). The percentiles are computed over the preceding 132 months and recomputed every month, so that no event is defined with information from the future. An episode is a sustained breach: it starts in the second of two consecutive months in breach, and $y_t = 1$ in that month. Booms and busts are defined for household credit, mortgage credit and house prices; only collapses are defined for household deposits and only increases for the impaired-advances ratio.

The 90th/10th percentile is a choice of tail, not an estimated threshold. For orientation, the SARB's Financial Stability Review reports a financial conditions index (FCI), standardised to zero mean and unit standard deviation. Unofficially, the SARB considers readings of its standardised FCI above about 0.5 or 1.0 to be stress. On the months that overlap with our sample, these correspond roughly to the 80th and 97th percentiles. Our 90th/10th definition lies

between them, and the $80^{th}/20^{th}$, $85^{th}/15^{th}$ and $95^{th}/5^{th}$ sensitivity analyses bracket both. Tail definitions of this kind have precedent. Lo Duca and Peltonen (2013) identify systemic events as episodes in which a stress index exceeds the 90th percentile of its distribution, and Alessi and Detken (2011) require a sustained breach (three consecutive quarters) of a threshold computed recursively from past data.

2.2 Data

2.2.1 Behavioural variables

Google searches are behavioural in the sense that they represent revealed behaviour – they record actions households take, and contrast with balance-sheet or price outcomes compiled by banks or statistical agencies, nor are they a survey of what households say. Search queries reveal what households are considering or worried about, and they are available for the month itself without a publication delay. Although search activity does not reveal the underlying intentions of individual households, it provides an observable signal of their behaviour.

Household financial behaviour evolves as households respond to changing financial conditions. Prior to entering the housing market, prospective borrowers acquire information about property purchases and mortgage finance. As financial pressures emerge, attention shifts towards debt-management and legal resolution mechanisms within the formal financial system. If access to formal credit becomes constrained, some households may instead seek alternative sources of liquidity through informal lenders. These distinct behavioural responses map to specific dimensions of macro-financial risks, as summarised in Figure 1.

To capture latent household financial behaviour, three behavioural indices using monthly high-frequency Google Trends search data are constructed. Google Trends measures the relative search volume (RSV) of user-defined search queries, capturing aggregate information-acquisition and attention. Previous research has highlighted that search-based indicators may perform poorly when search terms are selected in a purely data-driven manner or when underlying search behaviour changes over time (Lazer et al., 2014). To minimise these concerns, search terms were classified *a priori* according to their underlying behavioural mechanism before model estimation.

The taxonomy is grounded in the conceptual sequence through which households progress from housing search, to financial distress, and, where formal credit becomes unavailable, to informal credit substitution. Individual search terms were selected based on their semantic relevance to these behavioural channels rather than their statistical relationship with the dependent variables. Terms are grouped ex ante, before estimation, according to the underlying behavioural mechanism they represent. Specifically, we distinguish between (i)

housing and mortgage demand, (ii) formal financial distress, and (iii) informal credit substitution. Figure 1 illustrates these behavioural transmission channels.

We use search terms rather than Google's predefined topics. A term is a literal query that other researchers can replicate exactly. A topic is a grouping assigned by Google's algorithm, whose composition is not disclosed and may change over time. Terms also capture colloquial and local usage, such as "mashonisa", which a topic classification may not group as intended. Because individual terms can be noisy or miss synonyms, each index combines several terms, and the leave-one-out and sub-index checks in Section 3.4 show that the results do not depend on any single term. For example, setting Google Trends to the "COVID-19" topic and the period 2004–2019 returns non-zero search volume both worldwide and for South Africa, presumably because the topic also groups queries about earlier coronavirus outbreaks (accessed 23 October 2026).

Figure 1: The Household Credit Cycle



Housing and credit demand channel

The first behavioural indicator captures households' intentions to enter the housing and mortgage market. Because residential property purchases in South Africa are predominantly debt financed, searches relating to property acquisition (e.g., *property for sale*, *Property24*) and mortgage finance (e.g., *home loan application*, *bond calculator*, *pre-approval*) are interpreted as complementary manifestations of the same underlying behavioural process: the intention to purchase residential property. Accordingly, these search terms are combined into a single housing demand index that proxies the ex-ante build-up of macro-financial leverage and systemic vulnerabilities.

This index is intended to capture behavioural changes that precede realised housing transactions and mortgage origination, providing an early indication of shifts in housing demand and future household leverage before these are recorded in official housing market or banking statistics.

Formal financial distress channel

The second indicator captures household responses to worsening financial conditions within the formal financial system. As financial constraints intensify, households increasingly seek information on debt restructuring, legal remedies and default-related processes. Consequently, this index includes searches relating to debt review, sequestration, foreclosure, sheriff auctions and other formal debt-resolution mechanisms.

These searches are interpreted as behavioural manifestations of increasing financial distress that may precede subsequent deterioration in household credit performance and bank asset quality. The index therefore provides a real-time proxy for the emergence of financial stress before it becomes observable through conventional indicators such as impaired loans or non-performing loan ratios.

Informal credit substitution index (shadow structural stress)

In emerging markets, a critical but frequently unobserved dimension of financial instability is the migration of credit demand to informal lenders to meet short-term liquidity needs. Because these lending relationships operate largely outside the regulated financial system, they remain difficult for macroprudential authorities to monitor using conventional supervisory data. In South Africa, informal lenders continue to play an important role in providing short-term liquidity to financially constrained households, particularly where formal credit is unavailable or inaccessible (Krige, 2019). To proxy this behaviour, search terms associated with payday loans and informal lenders (e.g., *"mashonisas"*) are used. Consequently, the index provides a behavioural proxy for informal credit substitution and potential financial exclusion, offering information that complements conventional measures of household borrowing and banking sector conditions. The specific terms are summarised in Table 1.

Search term taxonomy and index construction

Table 1 outlines the complete taxonomy of the search terms used to construct the three BEWIs, categorizing each query by its structural role in the credit cycle.

Table 1: Google search term classification and credit cycle phases

BEWI	Housing and credit demand	Formal financial distress	Informal credit substitution
Credit cycle phase	Ex-ante build up	Ex-post realisation	Structural stress (shadow market)
Conceptual dimension	Speculative/organic credit expansion phase that captures the *build-up* of systemic vulnerability.	Balance sheet pressure and impending default and captures the *realization* of formal banking risk.	Substitution into informal, high-cost finance. Captures extreme household fragility and financial exclusion.
Search query groups	Attention: *property24; property24 for sale; private property; property; property for sale; houses near me; show houses near me; estate agent; remax; pam golding; seeff; buy house; buying a house*	Credit management: *home loan repayment; monthly payment; credit score; credit score check; itc check; itc credit check*	*mashonisa; mashonisa loans; loan shark; payday loan; fast loan; sassa loan*
	Credit intent: *home loan; mortgage; verband; home loan application; bond application; preapproval; qualify for home loan; home loan requirements; best home loan; fnb home loan; absa home loan; standard bank home loan; nedbank home loan; sa home loans; sa home loan application*	Debt resolution: *debt review; home loan debt review; debt consolidation; debt counselling;*	
	Affordability: *betterbond; ooba; transfer duty; transfer duties; transfer duty calculator; conveyancing fees; first home buyer; mortgage calculator; bond calculator; bond repayment calculator; flisp; bridging finance; home loan deposit; deposit for house; home affordability*	Mortgage default: *repossession; bank repossessed houses; properties in possession; repossession; foreclosure; sheriff auction; distressed sales; sequestration; garnishee order; missed payment; bond default*	

Notes: This table outlines the taxonomy of search query groups compiled to construct the BEWIs. Search queries were selected based on high-volume search terms in South Africa related to residential property acquisitions, banking debt management, and emergency liquidity. *Local context and terminology definitions: Informal credit terms: Mashonisa* refers to informal, unregistered moneylenders operating in South African townships and urban centers; *SASSA loan* refers to short-term micro-loans targeted at social grant recipients under the South African Social Security Agency.
Credit reporting terms: ITC check refers to credit bureau checks (historically named after the Information Trust Company, used colloquially for TransUnion credit reports). *Property & subsidy terms: FLISP* refers to the First-Time Home Finance subsidy (formerly Finance Linked Individual Subsidy Programme); *verband* is the Afrikaans term for mortgage/bond. *Lender & platform terms:* Major South African mortgage originators and commercial banks include *BetterBond*, *Ooba*, *FNB*, *ABSA*, *Standard Bank*, *Nedbank*, and *SA Home Loans*. All search volumes are extracted via Google Trends as monthly Relative Search Volume (RSV) series and aggregated into composite index categories

Aggregation and index construction

To construct the composite indices from the raw search query series, we apply an equal-weighting aggregation procedure to avoid over-reliance on any single query. Let $S_{i,t}$ be the raw relative search volume for query term i in month t. Google Trends rescales each downloaded series so that its maximum equals 100. To avoid using information from after month t, each term is rescaled at every date by the maximum of the series up to that date, as it would have appeared in a download ending in month t:

$$S_{i,t}^{rm} = 100 \cdot S_{i,t}/max_{s \le t} S_{i,s}$$

Because the absolute volumes of search terms can vary significantly based on linguistic popularity, we then standardise each individual series on its own history up to month t:

$$z_{i,t} = \left(S_{i,t}^{rm} - \mu_{i,t}\right)/\sigma_{i,t}$$

where $\mu_{i,t}$and $\sigma_{i,t}$ are the mean and standard deviation of $S_{i,s}^{rm}$for $s = 1, \dots, t$. The standardised series is defined from the twelfth observation onwards, and a term with no variation in its history to date is left out of the average at that date. The indices are therefore real-time: the value at month t uses data up to month t only. Because the standardisation uses the history to date, an index has no fixed mean over the sample; a negative mean means that its terms sit mostly below their own history to date.

The composite behavioural index $BEWI_{j,t}$ for category $j \in$ {Demand, Distress, Shadow} is then calculated as the simple average of its N_j constituent standardized search series:

$$BEWI_{j,t} = \frac{1}{N_j} \sum_{i=1}^{N_j} z_{i,t}$$

This aggregation approach ensures that each search query contributes equally to the signal, smoothing out idiosyncratic noise while preserving the underlying behavioural trend of the respective credit phase. We also use the equal-weight mean of the three indices, $BEWI^{All}t = \left(BEWI_{Demand,t} + BEWI_{Distress,t} + BEWI_{Shadow,t}\right)/3$.

Data limitations

A limitation of search-based behavioural indicators is that internet search activity may not fully represent all segments of the population. This is particularly relevant for the informal credit substitution index, as lower-income households – who are more likely to rely on informal lenders – may also have lower internet access or reduced digital engagement. Consequently, search intensity may understate the true extent of informal borrowing activity.

Econometrically, this digital divide introduces a potential measurement error which is likely to bias search-volume metrics downward. Consequently, the predictive performance of the shadow credit index should be interpreted as a conservative lower bound of the underlying relationship with systemic financial risk. This cannot be tested with the available data.

Google Trends data were downloaded once (with a fixed sample window), after the end of the sample. The real-time indices therefore reconstruct what each series would have shown at each date from that single download: they remove look-ahead in the scaling and

standardisation, but not the sampling noise in Google's data or any later change in how Google classifies queries. As with the existing literature, the analysis assumes that subsequent revisions to Google's normalisation procedure are limited, and do not materially affect the estimated relationships.

The underlying intent of searches is impossible to determine as searches may reflect both household decision-making and responses to media coverage.

Internet penetration increased over the sample period, potentially affecting the representativeness of Google search activity over time (World Bank, 2026). This may introduce measurement error, although this is partly mitigated because Google Trends reports relative rather than absolute search intensity.

2.2.2 Dependent variables

Eight events are defined on five outcome series (Table 2). Household credit boom has no episode in the forecast period and is not evaluated. The first outcome is banking fragility and it is measured in two ways. The impaired loans indicator captures the deterioration of bank asset quality using the ratio of impaired advances to total loans on banks' balance sheets (SARB, 2026). Higher values indicate a greater share of non-performing or impaired credit within bank loan portfolios, reflecting increasing borrower distress and heightened systemic banking vulnerability. The outcome is the monthly change in this ratio and the event is an unusually large increase.

The deposit contractions indicator measures systemic funding stress using the aggregate stock of household deposits held at South African banking institutions (SARB, 2026). Unlike savings flows, the stock of deposits represents the funding base of the banking system. Sharp contractions in household deposits therefore provide an indication of funding liquidity pressures and potential deposit runs. The outcome is the twelve-month log growth of the stock and the event is an unusually large contraction (a collapse).

The credit cycle is captured by two outcomes. Mortgage credit cycle events are identified using the value of new mortgage loans and re-advances granted for residential dwellings and flats (SARB, 2026). This measure captures new mortgage lending activity and therefore provides a timely indicator of expansions and contractions in residential mortgage credit. Broader household credit cycle events are based on total credit extended to households (SARB, 2026). This measure captures cyclical movements in aggregate household leverage beyond residential mortgages, including unsecured and other forms of retail lending. For both, the outcome is twelve-month log growth. The housing cycle is captured by house price booms and busts, identified using the national residential house price index published by Statistics

South Africa (2026b). House price booms reflect periods of rapid appreciation associated with the build-up of financial vulnerabilities, while busts capture market corrections that may amplify banking sector losses through declining collateral values. The index is published with a delay of at least five months (Table 2). The series enters the models with this delay of five months, so house price events are dated in the month the data become available.

2.2.3 Control variables

Each model is compared with a baseline built from conventional macro-financial indicators routinely monitored by central banks, in three nested information sets. The indicators are: SARB's policy repo rate (monthly change), capturing monetary policy conditions; consumer price inflation (Stats SA, 2026a), measuring inflationary pressures; the SARB composite leading business cycle indicator (monthly log growth); the credit-to-GDP gap, which captures the build-up of systemic credit imbalances; and the household debt-service ratio, the share of disposable income used to service debt.

The credit-to-GDP gap is the deviation of the log ratio of total credit (SARB) to GDP (Stats SA, 2026c) from a one-sided Hodrick-Prescott trend, estimated recursively so that the gap in month t uses data up to month t only. The smoothing parameter is 25 600 applied to monthly observations, in line with Msiska et al (2026). The gap is built as described: it is not the Basel calibration (Basel Committee on Banking Supervision, 2010) or the SARB's published gap, and the sensitivity analysis uses larger values of the smoothing parameter, including the monthly equivalents of the Ravn-Uhlig and Basel calibrations. GDP is the current vintage and is not revised in real time.

A fourth benchmark, "monthly macro", contains only the repo rate, inflation and the leading indicator. It has no credit or balance-sheet data and asks whether the indices add to what is available at monthly frequency.

Table 2 summarises the variables included in the empirical analysis, and the transformations implemented to reduce the influence of non-stationary trends, with the publication lag applied to each series. A control enters the model lagged by its publication delay, so the value used in month t is the latest one published by month t.

***Table 2:** Variables, sources and publication lags*

Variable	Source	Transformation	Lag (months)
Controls			
Repo rate	SARB	Monthly change	0
CPI inflation	Stats SA	Monthly change	1
SARB Leading Indicator (KBP7090N)	SARB	Monthly log growth	2
Credit-to-GDP gap (KBP1347M)	Authors; SARB credit, Stats SA GDP	one-sided HP gap of log ratio, λ = 25 600	1 (credit), 3 (GDP)
Debt-service ratio (KBP6289L)	SARB	Level, % of disposable income	3
Outcomes			
House prices	Stats SA	YoY log growth	5
Mortgage advances (KBP1470M)	SARB	YoY log growth	1
Household credit (KBP1505M)	SARB	YoY log growth	1
Household deposits (KBP1154M)	SARB	YoY log growth	1
Impaired advances (BA200)	SARB	Monthly change	1

Source: South African Reserve Bank (SARB), Statistics South Africa (Stats SA), and authors' calculations.

2.3 Estimation strategy

The conditional probability of this event is modelled using a standard cumulative logistic distribution:

$$P\left(Y_{t,h} = 1|\Omega_t\right) = \Lambda(\beta_0 + \beta_1{}'X_t + \beta_2 B_t)$$

where $\Lambda(z) = \frac{e^z}{1+e^z}$, Ω_t is the information set available to policy authorities at month t, X_t is a vector of conventional macro-financial control variables drawn from the information set (below), and B_t is a behavioural index added to the baseline: one of the Demand, Distress and Shadow indices, or a composite.

Three information sets define X_t. S0 has no controls: the baseline is an intercept-only model (the recursive base rate of events) and the index enters alone. S1 contains the credit-to-GDP gap. S2 contains all five controls. In S0 the baseline AUROC need not equal 0.5, because the base rate drifts, so the index is judged by its own AUROC against 0.5. Five additions are made one at a time to each information set: the Demand, Distress and Shadow indices, the composite of all three, and the composite of Demand and Distress. Cells in which the baseline AUROC is below 0.5 are marked with a dagger and not interpreted. All models are estimated by Firth's penalised maximum likelihood (Firth, 1993; Heinze and Schemper, 2002), because events are rare in every cell and separation is likely. Ordinary logit is a robustness check.

2.3.1 Real-time recursive scheme

The initial window is 60 months (January 2010 to December 2014), the first forecast is for January 2015, and the window then expands, with the model re-estimated every month. At each forecast origin the indices and controls are the real-time values (described above). Moreover, each control is lagged by its publication delay. At the forecast for month t, each outcome is used only up to month t−1, which matches its one-month publication delay; house prices are in addition lagged by their five-month delay. The exercise is quasi-real-time: every series respects its publication lag, but GDP is the current vintage and the Google Trends data were downloaded once, so later revisions are not reproduced. The event percentiles come from the 132 months up to that month, and the training sample consists of earlier origins whose forward window is fully observed by then or contains an observed episode start. The forecast is the probability that an episode starts within h months. The initial window of 60 months was chosen after inspecting full-sample results; the sensitivity analysis varies it.

2.3.2 Evaluation

Model performance is evaluated out of sample. In-sample coefficients (Table 4) show whether the indices carry information, but the primary objective of an EWS is to correctly discriminate between periods that precede distress events and tranquil periods (Borio and Drehmann, 2009; Alessi and Detken, 2011). Classification performance is assessed using the Area Under the Receiver Operating Characteristic Curve (AUROC), which measures the model's ability to distinguish between crisis and non-crisis observations across all possible probability thresholds. AUROC is computed on the pooled forecasts of each model at each horizon, with the 95 percent interval of DeLong et al. (1988).

The incremental contribution of each BEWI is evaluated by comparing the performance of the baseline macro-financial model with models augmented by each addition, on the same forecast origins. We report the change in AUROC with the paired DeLong test, and the Clark and West (2007) test on the Brier loss with a Newey and West (1987) variance (bandwidth equal to h). p-values are adjusted by the Benjamini and Hochberg (1995) procedure within each information set. Given the overlap between forecast windows, DeLong test results are interpreted cautiously. In each cell, the index with the highest AUROC over the whole forecast period is called the best BEWI. This selection may overstate out-of-sample performance because the index is selected and evaluated on the same forecasts. The final segment is the period from August 2023 to the end of the sample (about 30 forecast months at the 3-month horizon, fewer at longer horizons), evaluated once, with the index in each cell chosen on the

earlier forecasts only. Its length, 36 months of the forecast grid, was fixed before the results were seen; a 48-month alternative was added afterwards.

2.4 Robustness and sensitivity

To assess the reliability of the early warning signals, the main results are subjected to six groups of sensitivity and robustness exercises. For event definitions, the percentile is varied to the $85^{th}/15^{th}$, $80^{th}/20^{th}$ and $95^{th}/5^{th}$ (the last leaves some outcomes without episodes), the persistence rule to one and three months, and the percentile window to 96 months and to an expanding window. For estimation, the initial window is shortened to 48 and lengthened to 84 months, ordinary logit replaces Firth's estimator, and the baseline also contains the outcome's own lagged value (lagged by its publication delay). For information timing, controls enter with no publication lag and with lags one month longer, and the smoothing parameter of the credit-to-GDP gap is raised to 400 000, 2 073 600 and 32 400 000. As a placebo, the indices are shifted in time by 48, 96 and 144 months, which should remove any predictive content.

Two further groups examine the behavioural indices and the evaluation. The aggregate indices are replaced with sub-indices (housing attention, mortgage intent and affordability searches for housing and credit demand; credit management, debt resolution and mortgage default for formal financial distress), which shows whether the results are driven by the overall behavioural channel or by sub-categories of search activity. Leave-one-out analyses are also performed. Finally, without re-estimating, the stored forecasts are re-evaluated (a) without origins at which an episode is already under way, (b) additionally without the 12 months after, and (c) without the COVID months (March 2020 to December 2021).

3 Results

3.1 Descriptive statistics

Table 3 reports summary statistics for January 2010 to December 2025. Following standard transformations to induce stationarity, the macro-financial variables exhibit considerable cyclical variation over the sample period, reflecting alternating phases of credit expansion, housing market activity and banking sector stress. For example, the asset quality indicator (change in impaired loans) ranges from −0.24 to 0.42 percentage points with positive skewness (0.66): sudden, sharp deteriorations are followed by protracted periods of gradual recovery. Mortgage advances growth is by far the most volatile outcome (standard deviation 24 per cent, against about 2 per cent for household credit and deposits) because it is the growth of the monthly value of new loans granted, not of an outstanding stock.

The behavioural indices are the real-time versions, standardised on their own history to date, so their means are not zero. The Distress index is the least variable (standard deviation

0.23) and the Shadow index the most (0.38); the Demand index has the widest range (−1.63 to 0.64), with its lowest readings before 2015. The indices carry different information (Appendix Table A3): Demand and Distress are positively correlated (0.57), while Shadow is negatively correlated with Demand (−0.35) and essentially uncorrelated with Distress (0.04). The same pattern holds over the forecast period (Appendix Table A3). This supports treating them as distinct channels in the early warning analysis.

Table 3: Descriptive statistics, January 2010 to December 2025

Variable	Unit	N	Mean	SD	Min	Median	Max	Skew
Behavioural indices (real time)								
Demand index	z-score	181	−0.371	0.338	−1.628	−0.384	0.643	0.09
Distress index	z-score	181	−0.274	0.232	−1.083	−0.248	0.449	−0.31
Shadow index	z-score	169	0.100	0.385	−0.827	0.126	0.897	−0.34
Composite (mean of three indices)	z-score	191	−0.187	0.189	−0.817	−0.188	0.317	−0.11
Controls (lagged to publication date)								
Change in repo rate	pp, monthly change	191	−0.001	0.170	−1.181	0.000	0.614	−1.25
Change in CPI inflation	pp, monthly change	189	−0.015	0.207	−0.800	0.000	0.700	−0.16
Growth of leading indicator	monthly log change	189	0.0009	0.0125	−0.0613	−0.0008	0.0455	0.02
Credit-to-GDP gap	log points	166	0.0019	0.0289	−0.0866	0.0043	0.1687	1.63
Debt service ratio	% of disposable income	189	8.74	0.84	6.80	8.60	10.60	0.23
Outcomes								
Change in impaired advances	pp, monthly change	189	−0.006	0.090	−0.240	−0.010	0.420	0.66
Household credit growth	% y/y	180	4.88	1.99	0.42	4.66	9.86	0.22
Household deposit growth	% y/y	180	8.86	2.26	2.31	8.78	13.31	−0.32
Mortgage advances growth	% y/y	177	2.79	24.05	−76.23	4.48	133.03	0.89
House price growth	% y/y	175	4.73	1.78	1.45	4.91	7.80	−0.16

Notes: The behavioural indices are the real-time versions: each search term is rescaled by its running maximum and standardised on its own history up to the date (at least 12 months), therefore the means need not be zero; a negative mean means the terms sit mostly below their own history to date. pp = percentage points; y/y = 12-month log growth in per cent; credit-to-GDP gap = one-sided HP gap of the log ratio (λ = 25 600). Skew = moment skewness. The Demand and Distress indices start in December 2010, the Shadow index and the composite in December 2011, and the credit-to-GDP gap in March 2012.

3.2 In-sample estimates

Table 4 reports Firth estimates fitted once on the full sample at the 12-month horizon, with and without the best BEWI, for each of the eight events. The index added is the one with the highest out-of-sample AUROC for that outcome in Table 6 (information set S2). The estimates are descriptive; the evidence on forecasting is in Section 3.3. Adding the index improves the in-sample fit for seven of the eight events: the likelihood-ratio test is significant at the 5 per cent level or better, except for the mortgage credit bust (LR = 1.41). The gains in AUROC are largest for deposit collapses (0.710 to 0.867) and house price booms (0.640 to 0.796).

In six of the seven significant cases the sign is the one the channel predicts: rising Shadow or Distress searches (stress) go with banking fragility and busts, and rising Demand

searches go with booms. Higher Shadow-index values raise the probability of a deposit collapse ($\beta = 4.20$, $p < 0.01$) and of a rise in impaired advances ($\beta = 1.59$, $p < 0.05$). Higher Demand-index values raise the probability of a mortgage credit boom ($\beta = 2.32$, $p < 0.05$) and of a household credit boom ($\beta = 1.83$, $p < 0.05$; in-sample only). Higher Distress-index values raise the probability of a house price bust ($\beta = 2.76$, $p < 0.01$) and lower that of a house price boom ($\beta = -3.80$, $p < 0.01$). The exception is the household credit bust, where a higher Distress index is associated with a lower probability of a bust ($\beta = -3.35$, $p < 0.01$). The p-values are for the index selected as the best of three and are not adjusted for that selection, so they are somewhat optimistic.

In-sample AUROCs are much higher than the out-of-sample values reported beneath them in Table 4, although the two are not strictly comparable because the in-sample cutoff is fixed for the whole sample. The evidence on forecasting is in Section 3.3.

Table 4: In-sample estimates at the 12-month horizon, with and without the best BEWI

	Impaired		Deposits (collapse)		Mortgage credit boom		Mortgage credit bust		Household credit boom		Household credit bust		House price boom		House price bust	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Repo	0.274	-1.175	2.693*	-0.350	-14.212***	-11.522***	2.204*	2.772**	3.353**	4.954***	2.193	2.033	0.988	1.086	3.597**	4.118***
	(1.147)	(1.277)	(1.418)	(1.802)	(3.502)	(3.278)	(1.231)	(1.333)	(1.462)	(1.685)	(1.453)	(1.469)	(1.054)	(0.981)	(1.401)	(1.479)
Cpi	0.138	-0.423	1.147	0.813	-2.700	-2.739	0.297	0.277	2.341**	2.474**	-0.249	-0.148	-0.459	-0.303	0.268	0.285
	(1.234)	(1.316)	(1.173)	(1.320)	(1.687)	(1.700)	(1.145)	(1.140)	(1.162)	(1.202)	(1.230)	(1.312)	(0.994)	(1.040)	(1.260)	(1.251)
Business cycle	-52.291***	-56.528***	-18.566	-12.362	48.769***	51.744***	-24.436	-21.469	-42.057***	-40.441***	16.418	9.710	19.590	20.031	-35.204	-32.782
	(18.839)	(19.391)	(17.437)	(19.383)	(18.295)	(19.273)	(15.307)	(15.085)	(14.953)	(15.095)	(18.889)	(19.842)	(13.928)	(14.485)	(19.450)	(20.652)
Credit gap	16.369*	21.100**	-39.443***	-54.191***	24.621***	17.691*	10.460	6.729	15.462*	9.524	-8.568	-19.192	-5.010	-6.874	8.812	9.108
	(8.471)	(8.946)	(12.984)	(15.161)	(9.181)	(10.647)	(6.908)	(7.515)	(7.599)	(8.242)	(9.891)	(12.999)	(7.117)	(8.111)	(7.629)	(7.554)
Debt service ratio	-0.351	-0.459	0.159	0.099	-2.445***	-2.169***	-0.269	-0.125	-1.698***	-1.403***	0.337	0.471	-0.614**	-0.723**	1.252***	1.273***
	(0.326)	(0.312)	(0.325)	(0.327)	(0.622)	(0.682)	(0.296)	(0.324)	(0.437)	(0.439)	(0.282)	(0.315)	(0.270)	(0.306)	(0.284)	(0.288)
Intercept	1.377	2.100	-3.225	-3.694	18.220***	16.498***	0.864	-0.056	13.233***	11.269***	-4.749*	-7.024**	4.495**	4.258	-12.592***	-12.119***
	(2.792)	(2.657)	(2.883)	(2.964)	(5.068)	(5.580)	(2.536)	(2.688)	(3.665)	(3.641)	(2.502)	(2.912)	(2.315)	(2.593)	(2.585)	(2.593)
BEWI coefficient		1.586**		4.200***		2.316**		0.893		1.832**		-3.353***		-3.801***		2.756***
		(0.749)		(1.023)		(1.085)		(0.747)		(0.802)		(1.061)		(0.937)		(1.052)
Best BEWI		Shadow		Shadow		Demand		Demand		Demand		Distress		Distress		Distress
LR		4.695**		22.769***		4.295**		1.411		5.533**		10.347***		20.195***		7.217***
Obs	152	152	161	161	151	151	151	151	157	157	157	157	155	155	155	155
Events	26	26	27	27	23	23	30	30	41	41	22	22	50	50	32	32
AIC	137.492	134.534	135.715	113.007	79.127	76.176	154.166	154.662	144.534	140.505	135.232	125.867	190.358	171.054	136.134	130.483
McFadden R^2	0.098	0.133	0.150	0.320	0.479	0.518	0.056	0.066	0.265	0.298	0.031	0.121	0.085	0.194	0.214	0.262
AUROC (in-sample)	0.733	0.769	0.710	0.867	0.942	0.939	0.662	0.699	0.803	0.842	0.652	0.753	0.640	0.796	0.758	0.821
AUROC (out-of-sample)	0.441†	0.455†	0.357†	0.381†	0.637	0.665	0.440†	0.443†	n/a	n/a	0.764	0.781	0.595	0.675	0.220†	0.203†
N (out-of-sample)	118	118	127	127	117	117	117	117	n/a	n/a	123	123	121	121	121	121
Events (out-of-sample)	57	57	45	45	28	28	30	30	n/a	n/a	38	38	7	7	46	46

Notes: Firth penalised-likelihood logit fitted once on the full sample at the 12-month horizon. The dependent variable is 1 if a sustained boom or bust (two consecutive months beyond the 90th or 10th percentile of the outcome over the last 132 months of the sample) occurs within the next 12 months. Baseline columns contain the change in the repo rate, the change in CPI, growth of the SARB leading business-cycle indicator, the credit-to-GDP gap and the debt service ratio, each lagged to its publication date. + BEWI columns add the single search-based index (Demand, Distress or Shadow) with the highest out-of-sample AUROC for that outcome at 12 months in Table 6 (information set S2); household credit boom has no out-of-sample events, so its index (Demand) is imposed, because there are no out-of-sample events from which to select one, and the column is in-sample only. Standard errors in parentheses; stars from profile penalised-likelihood p-values (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). LR χ^2 is the chi-square(1) statistic of the BEWI term from the same test. AIC and McFadden R^2 use the ordinary logistic log-likelihood at the Firth estimates. McFadden's pseudo-R^2, likelihood-ratio tests and the AIC are reported here only and play no part in the out-of-sample evaluation. Observations differ across outcomes because trailing months whose 12-month window is not fully observed are dropped, not counted as non-events. In-sample AUROC uses a single cutoff for the whole sample and is not comparable with the out-of-sample AUROC in the lower block, which comes from the recursive forecasts of Table 5 (cutoff re-estimated at every forecast origin, so the events differ). † = out-of-sample baseline AUROC below 0.5 (not interpreted); n/a = no out-of-sample events.

3.3 Predictive performance of behavioural early indicators

This section asks two questions of the real-time out-of-sample forecasts. How far ahead do the indices see on their own? Figure 2 and Table 5 answer this. Do they add to what a macro model already knows? Table 6 compares each baseline with the baseline plus the best of the three indices, and Table 7 repeats the comparison on a final segment that was held back.

Search behaviour picks up household stress early. Against the credit-to-GDP gap and the monthly macro indicators, the search indices rank higher in six of the seven outcomes, most clearly at one to eight months ahead (Figure 2). For household credit busts, deposit collapses and house price booms the signal is also statistically clear; for the other outcomes it is suggestive only.

In short, the indices carry a real-time signal on their own and complement macro data. For the household credit bust the Demand and Distress indices are informative up to 10 and 8 months ahead. For deposit collapses the Shadow index is informative up to 12 months ahead and outperforms the credit-to-GDP gap at 12 and 24 months, where the five macro controls have no skill (AUROC below 0.5). House price booms show the same pattern for Distress, though on few events. Added to the credit-to-GDP gap, the best index raises the household credit bust AUROC significantly. Added to all five controls, which already forecast that outcome well, the gain is small (at most 0.033). The final segment is too short to test these results either way: it holds one household credit bust and no booms.

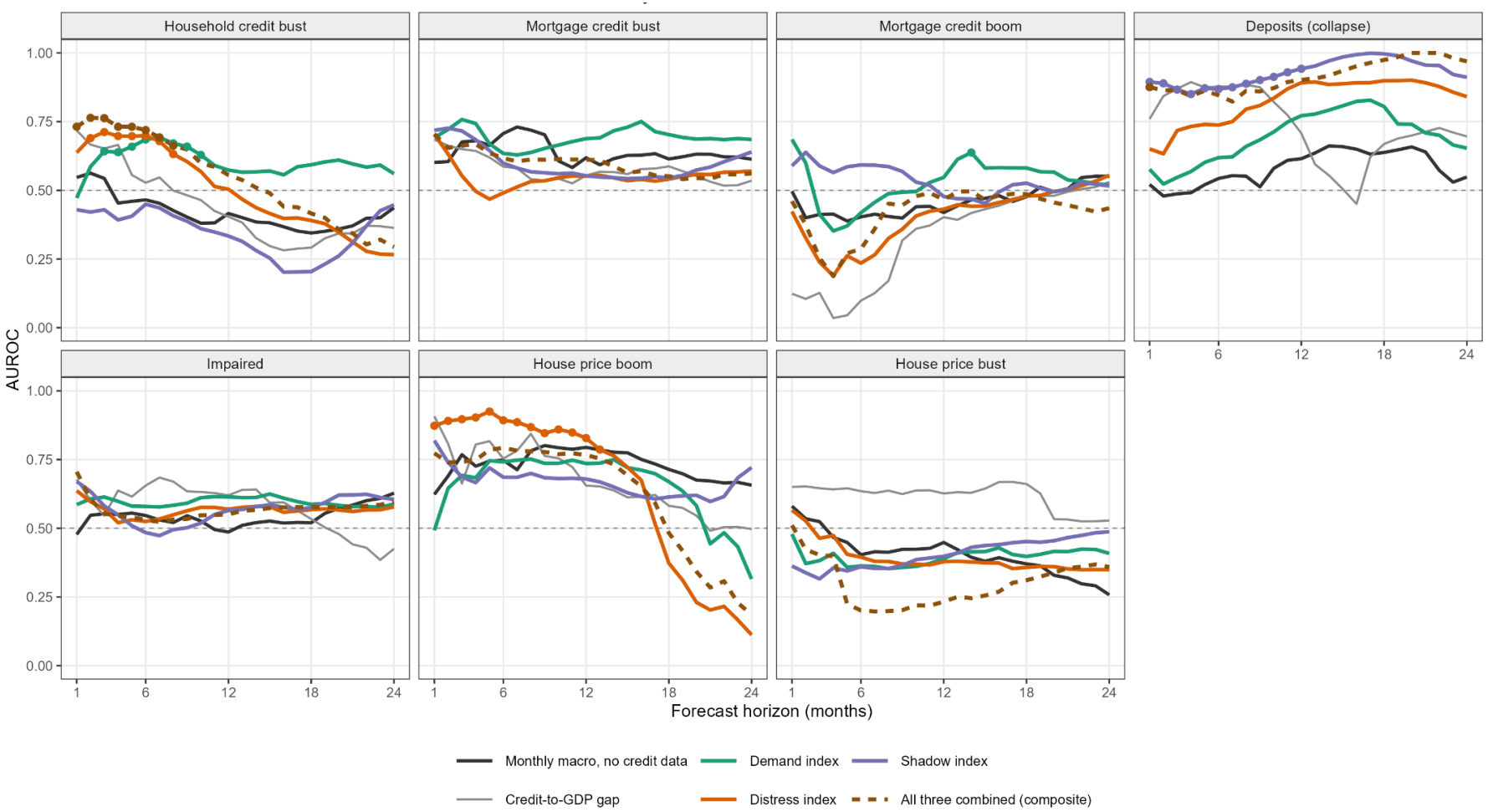
Figure 2 shows the AUROC of each indicator on its own at every horizon from 1 to 24 months, and Table 5 gives the values at 3, 6, 12 and 24 months for all seven outcomes with out-of-sample events, together with the horizons at which each indicator passes both tests (Appendix Table A1 has the combinations with the gap and with the controls).

For the household credit bust, the Demand and Distress indices carry a signal from 3 to 10 and from 2 to 8 months ahead (the dots in Figure 2), and not beyond. At longer horizons they do worse than a coin toss: the Distress index is significantly below 0.5 from 19 months, and the Shadow index is below 0.5 throughout, significantly so from 10 to 22 months. The five macro controls see further, with an AUROC of 0.746 to 0.939. At 3 and 6 months the Distress index (0.712 and 0.699) is not significantly different from them, and adding any index to the controls changes the AUROC by less than 0.04 (Appendix Table A1, Panel C).

For deposit collapses, the Shadow index passes both tests from 1 to 12 months and is the best indicator at 12 and 24 months (0.943 and 0.911). At 3 and 6 months the credit-to-GDP gap does as well (0.870 and 0.878, against 0.867 and 0.868), while the five controls have no skill at any horizon (AUROC below 0.5). Combining the Shadow index with the gap or with

the controls lowers the AUROC compared with the Shadow index alone (Appendix Table A1, Panels B and C). Shadow values close to 1.0 at 16 to 22 months come from labelled months arriving in blocks and overstate precision.

Figure 2: How far ahead each indicator sees (stand-alone AUROC by forecast horizon)



Notes: Stand-alone AUROC of each indicator by forecast horizon. Real-time out-of-sample forecasts; each indicator on its own; event = an episode starts within the next h months. Dashed horizontal line = 0.5 (a coin toss). Coloured lines: the behavioural indices (dots: the 95% DeLong interval excludes 0.5 and the Clark–West test against the constant forecast has $p < 0.05$); grey lines: benchmarks. 'Monthly macro' = repo rate, CPI and leading indicator together (no credit or balance-sheet data); the credit-to-GDP gap, the debt service ratio and the five controls together use credit and household balance-sheet data. DeLong treats the overlapping monthly forecasts as independent and is generous; neighbouring horizons share most of their information. Event counts by outcome are in Table 6; the months labelled positive come in blocks, so the number of independent episodes is much smaller. The debt service ratio and the five controls together are in Appendix Figure A1 and Table A1.

Table 5: Stand-alone AUROC of each indicator, by horizon, for the seven outcomes with out-of-sample events

Outcome	Indicator	3m	6m	12m	24m	Passes both tests (months)
Impaired	Credit-to-GDP gap	0.546	**0.656***	**0.620***	0.425	none
	Demand index	**0.614**	0.579	0.614*	0.588	none
	Distress index	0.570	0.525	0.569	0.578	none
	Shadow index	0.581	0.484	0.565	**0.605**	none
	Five macro controls	0.569	0.498	0.441	0.398	none
	Origins (events)	*127 (27)*	*124 (39)*	*118 (57)*	*106 (84)*	
Deposits (collapse)	Credit-to-GDP gap	**0.870***	**0.878***	0.708*	0.696*	none
	Demand index	0.547	0.619*	0.772*	0.653*	none
	Distress index	0.718*	0.737*	0.892*	0.841*	none
	Shadow index	0.867*	0.868*	**0.943***	**0.911***	1–12
	Five macro controls	0.494	0.447	0.357	0.295	none
	Origins (events)	*132 (30)*	*132 (38)*	*127 (45)*	*115 (54)*	
Mortgage credit boom	Credit-to-GDP gap	0.127	0.099	0.402	0.530	none
	Demand index	0.412	0.418	0.547	0.519	14
	Distress index	0.239	0.235	0.431	0.555	none
	Shadow index	0.589	0.592	0.477	0.516	none
	Five macro controls	**0.670***	**0.683***	**0.582**	**0.697***	15–24
	Origins (events)	*113 (18)*	*110 (22)*	*104 (28)*	*92 (40)*	
Mortgage credit bust	Credit-to-GDP gap	0.650	0.586	0.554	0.535	none
	Demand index	**0.758***	**0.634***	**0.688***	**0.685***	none
	Distress index	0.553	0.490	0.552	0.570	none
	Shadow index	0.716*	0.599	0.553	0.640*	none
	Five macro controls	0.599	0.508	0.440	0.602	none
	Origins (events)	*126 (14)*	*123 (18)*	*117 (30)*	*105 (52)*	
Household credit bust	Credit-to-GDP gap	0.652*	0.528	0.404	0.363	1
	Demand index	0.642*	0.685*	0.574	0.560	3–10
	Distress index	0.712*	0.699*	0.504	0.266	2–8
	Shadow index	0.429	0.449	0.334	0.447	none
	Five macro controls	**0.776***	**0.746***	**0.764***	**0.939***	1–5, 7–24
	Origins (events)	*132 (22)*	*129 (28)*	*123 (38)*	*115 (44)*	
House price boom	Credit-to-GDP gap	0.663	0.754*	0.655	0.497	none
	Demand index	0.692	0.742	0.736	0.315	none
	Distress index	**0.897***	**0.893***	**0.828***	0.112	1–13
	Shadow index	0.687*	0.686*	0.679*	**0.721***	none
	Five macro controls	0.879*	0.682	0.595	0.473	none
	Origins (events)	*130 (4)*	*127 (7)*	*121 (7)*	*109 (7)*	
House price bust	Credit-to-GDP gap	**0.646***	**0.635***	**0.627***	**0.528**	none
	Demand index	0.382	0.363	0.389	0.408	none
	Distress index	0.464	0.395	0.379	0.349	none
	Shadow index	0.316	0.360	0.398	0.487	none
	Five macro controls	0.572	0.451	0.220	0.318	1
	Origins (events)	*130 (28)*	*127 (34)*	*121 (46)*	*113 (68)*	

Notes: Each cell is the AUROC of the indicator at the forecast horizon in the column head (real-time recursive Firth logit, first forecast Jan 2015). The indicators of an outcome are compared on the same forecast origins, which are also common to the no-controls constant forecast. * = the 95% DeLong interval excludes 0.5. Bold = highest AUROC of the outcome at that horizon; grey = the highest or not significantly different from it (paired DeLong test, two-sided $p \geq 0.05$). The credit-to-GDP gap is information set S1, each index on its own is S0, and the five macro controls together are S2. Passes both tests (months): the horizons, from 1 to 24 months, at which the 95% DeLong interval excludes 0.5 and the Clark–West test against the constant forecast has $p < 0.05$; these are the dots in Figure 2. Overlapping monthly labels make the DeLong stars generous and the 'not different' marking conservative. The household credit boom has no out-of-sample events and is not shown. Combinations of the gap and of the controls with the indices are in Appendix Table A1.

House price booms also show a strong Distress result. The Distress index passes both tests from 1 to 13 months (0.897, 0.893 and 0.828 at 3, 6 and 12 months), but with four to seven events this is an illustration, not evidence. For mortgage credit busts the Demand index has the highest AUROC of the five indicators at all four horizons (0.634 to 0.758, against 0.535 to 0.650 for the gap) and is above 0.5 on the DeLong test at every horizon, but at no horizon on the Clark–West test. For house price busts none of the three indices is above 0.5 at 3, 6, 12 or 24 months. For impaired advances no index passes both tests at any horizon, and for mortgage credit booms only the Demand index does, at 14 months.

The indices add to macro data at little cost (Table 6). Adding the best index raises the AUROC in 25 of the 28 cells with the five controls (S2); the three decreases are small (at most 0.019) and none is significant ($p \geq 0.086$). Against the credit-to-GDP gap it raises the AUROC in 21 of 28 cells; of the seven decreases, three are significant (impaired advances at 6 months, deposit collapses at 6 and 12 months). The gains are small. Against the credit-to-GDP gap, which is itself below 0.5 in seven of the 28 cells, the best index adds up to 0.158 AUROC where the baseline is above 0.5 and there are more than seven events. Against the five controls it adds 0.033 or less in the same cells. The gain is statistically significant ($p < 0.05$) in five of the 28 S2 cells and has $q < 0.10$ in three. In 12 of the S2 cells the five controls are themselves below 0.5; in the other 16 the index raises the AUROC in 14. The household credit boom has no out-of-sample events and cannot be evaluated. Because the best of the three indices is chosen on the forecasts it is evaluated on, these gains are an upper bound.

Table 6: Out-of-sample AUROC of baseline and baseline + BEWI models, by information set and horizon

			S0: no controls		S1: credit-to-GDP gap					S2: five macro controls				
Outcome	Months	N (events)	Index	BEWI alone	Index	Gap	+ BEWI	Δ AUROC	q	Index	Macro	+ BEWI	Δ AUROC	q
Impaired	3	127 (27)	Dem	0.614	Dem	0.546	0.573	+0.027	0.607	Dem	0.569	0.573	+0.004	0.576
	6	124 (39)	Dem	0.579	Dis	0.656	0.630	−0.026	–	Dem	0.498†	0.524	+0.026	–
	12	118 (57)	Dem	0.614	Sha	0.620	0.647	+0.027	0.627	Sha	0.441†	0.455	+0.014	–
	24	106 (84)	Sha	0.605	Dis	0.425†	0.476	+0.050	–	Dis	0.398†	0.404	+0.006	–
Deposits (collapse)	3	132 (30)	Sha	0.867	Dis	0.876	0.805	−0.070	–	Sha	0.497†	0.574	+0.078	–
	6	132 (38)	Sha	0.868	Dis	0.879	0.760	−0.119	–	Sha	0.445†	0.505	+0.060	–
	12	127 (45)	Sha	0.943	Dem	0.708	0.670	−0.038	–	Sha	0.357†	0.381	+0.024	–
	24	115 (54)	Sha	0.911	Dis	0.696	0.682	−0.015	–	Dis	0.295†	0.296	+0.002	–
Mortgage credit boom	3	126 (18)	Sha	0.608	Dem	0.184†	0.318	+0.134	–	Sha	0.655	0.663	+0.007	0.931
	6	123 (22)	Sha	0.620	Dem	0.188†	0.404	+0.216	–	Dis	0.687	0.668	−0.019	–
	12	117 (28)	Dem	0.613	Dem	0.458†	0.565	+0.107	–	Dem	0.637	0.665	+0.027**	0.078
	24	105 (40)	Dis	0.644	Dem	0.624	0.701	+0.077***	0.002	Dis	0.758	0.774	+0.017	0.469
Mortgage credit bust	3	126 (14)	Dem	0.758	Sha	0.650	0.711	+0.061**	0.072	Dem	0.599	0.608	+0.008	0.739
	6	123 (18)	Dem	0.634	Sha	0.586	0.625	+0.039*	0.163	Sha	0.508	0.518	+0.010	0.798
	12	117 (30)	Dem	0.688	Sha	0.554	0.608	+0.054**	0.055	Dem	0.440†	0.443	+0.002	–
	24	105 (52)	Dem	0.685	Sha	0.535	0.563	+0.028	0.711	Sha	0.602	0.626	+0.023*	0.185
Household credit boom	3–24	*n/e: no events in the out-of-sample period, so no forecast can be evaluated*												
Household credit bust	**3**	132 (22)	Dis	0.712	Dis	0.652	0.742	+0.090***	0.012	Dis	0.776	0.802	+0.027**	0.138
	6	129 (28)	Dis	0.699	Dis	0.528	0.686	+0.158***	0.001	Dis	0.746	0.780	+0.033***	0.074
	12	123 (38)	Dem	0.574	Dis	0.404†	0.548	+0.144	–	Dis	0.764	0.781	+0.017	0.649
	24	115 (44)	Dem	0.560	Dem	0.363†	0.569	+0.205	–	Dem	0.939	0.932	−0.007	–
House price boom	3	130 (4)	Dis	0.897	Dis	0.663	0.913	+0.250	0.201	Dis	0.879	0.915	+0.036**	0.125
	6	127 (7)	Dis	0.893	Dis	0.754	0.892	+0.138	0.234	Sha	0.682	0.789	+0.107	0.420
	12	121 (7)	Dis	0.828	Dis	0.655	0.914	+0.258***	0.012	Dis	0.595	0.675	+0.080	0.336
	24	109 (7)	Sha	0.721	Sha	0.497†	0.664	+0.167	–	Sha	0.473†	0.604	+0.130	–
House price bust	3	130 (28)	Dis	0.464†	Dis	0.646	0.639	−0.007	–	Dem	0.572	0.594	+0.022**	0.078
	6	127 (34)	Dis	0.395†	Dis	0.635	0.638	+0.003	0.943	Dem	0.451†	0.470	+0.019	–
	12	121 (46)	Sha	0.398†	Dis	0.627	0.648	+0.021	0.332	Dis	0.220†	0.203	−0.018	–
	24	113 (68)	Sha	0.487†	Dis	0.528	0.524	−0.004	–	Sha	0.318†	0.351	+0.033	–

Notes: Quasi-real-time out-of-sample AUROC. Models are re-estimated every month with a Firth penalised logit on information available at the time (initial window 60 months, first forecast January 2015; publication lags respected). An event is a sustained boom or bust: two consecutive months beyond the 90th or 10th percentile of the outcome over the preceding 132 months; the forecast target is an event starting within 3, 6, 12 or 24 months. S1 baseline (Gap): credit-to-GDP gap only. S2 baseline (Macro): change in repo rate, change in CPI, growth of the SARB leading indicator, credit-to-GDP gap and debt service ratio. + BEWI adds the single search-based index (Dem = Demand, Dis = Distress, Sha = Shadow) with the highest AUROC in the cell, chosen on AUROC and never on p-values. The index is the best of three on these same forecasts, so the gains are an upper bound; Table 7 chooses it on earlier forecasts only. S0 has no controls: the intercept-only model's AUROC is not 0.5 because the training base rate drifts, so BEWI alone is judged against 0.5 and no baseline is shown. Δ AUROC = + BEWI minus baseline. Stars: DeLong test of + BEWI against the baseline on the same forecast origins (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$); because event labels overlap across adjacent months the p-values are probably too small. q = Benjamini–Hochberg q-value within each information set over all 84 single-index tests; shaded cells have $q < 0.10$. † = baseline AUROC below 0.5 (S0: BEWI alone not above 0.5), so the comparison is not interpreted; stars and q are not shown where the baseline is below 0.5 or $\Delta \leq 0$ (–). Bold months: BEWI alone exceeds 0.5 in S0 and + BEWI significantly improves on the baseline ($p < 0.05$, $\Delta > 0$, baseline ≥ 0.5) in both S1 and S2. N (events) = months forecast in the S2 sample and months labelled as events. n/e = not estimable.

The clearest evidence of incremental predictive information concerns household credit busts. At the 3- and 6-month horizons, the Distress index alone achieves AUROCs of 0.712 and 0.699, respectively. Adding the index to the credit-to-GDP gap raises the AUROC from 0.652 to 0.742 at 3 months and from 0.528 to 0.686 at 6 months ($q = 0.012$ and 0.001). The gains over the five-control model are smaller: the AUROC increases from 0.776 to 0.802 at 3 months and from 0.746 to 0.780 at 6 months ($q = 0.138$ and 0.074). This is the only outcome where the index is above 0.5 on its own and significantly improves ($p < 0.05$) on both the gap and the five controls (bold in Table 6). Thus, the evidence of incremental predictive value is stronger relative to the credit-to-GDP gap than relative to the full set of controls. At 12 and 24 months, the changes in AUROC relative to the five-control model are negligible (+0.017 and −0.007). The in-sample estimates in Table 4 are for the 12-month horizon, where the index does not add significantly to the five controls out of sample.

For the other outcomes, gains are generally small or cannot be interpreted. For deposit collapses, adding an index to the credit-to-GDP gap reduces the AUROC by 0.015 to 0.119. Comparisons with the five-control model are not interpreted because its AUROC is below 0.5. For house price booms, gains over the five-control model are larger (0.036 to 0.130), but are based on only four to seven events. For impaired advances, mortgage credit busts and booms, and house price busts, gains are 0.033 or less, with $q < 0.10$ in only two cells: mortgage credit boom at 12 months and house price bust at 3 months.

Table 7 evaluates performance over the final 36 months of the sample, from August 2023 onwards, with the index in each cell selected using earlier forecasts only. Because the search indices end in December 2025, this segment contains approximately 30 forecast months at the 3-month horizon and fewer at longer horizons. It includes one household credit bust, beginning in early 2025, and no booms, limiting the conclusions that can be drawn from this evaluation. The Distress index itself achieves AUROCs of 0.775 at 6 months and 0.698 at 12 months for household credit busts, although this result rests on a single episode. In this window the credit-to-GDP gap alone ranks months worse than chance (AUROC 0.358 and 0.219 for household credit busts at 6 and 12 months, and 0.307 for deposit collapses at 3 months). Adding the index lifts the combined model above 0.5 in all three cells (0.750, 0.688 and 0.529; $p = 0.007$ to 0.037, $q = 0.042$ to 0.099). Because the baseline is below 0.5 this is not a test of incremental information, but it shows the index supplying signal where the gap fails. No index improves significantly on the five-control model ($q \geq 0.808$), and the five-control baseline AUROC is below 0.5 in five of the seven cells reported. For deposit collapses, the Shadow

index performs less well in the final segment, with AUROCs of 0.569 at 3 months and 0.377 at 6 months, compared with 0.867 and 0.868 over the full forecast sample.

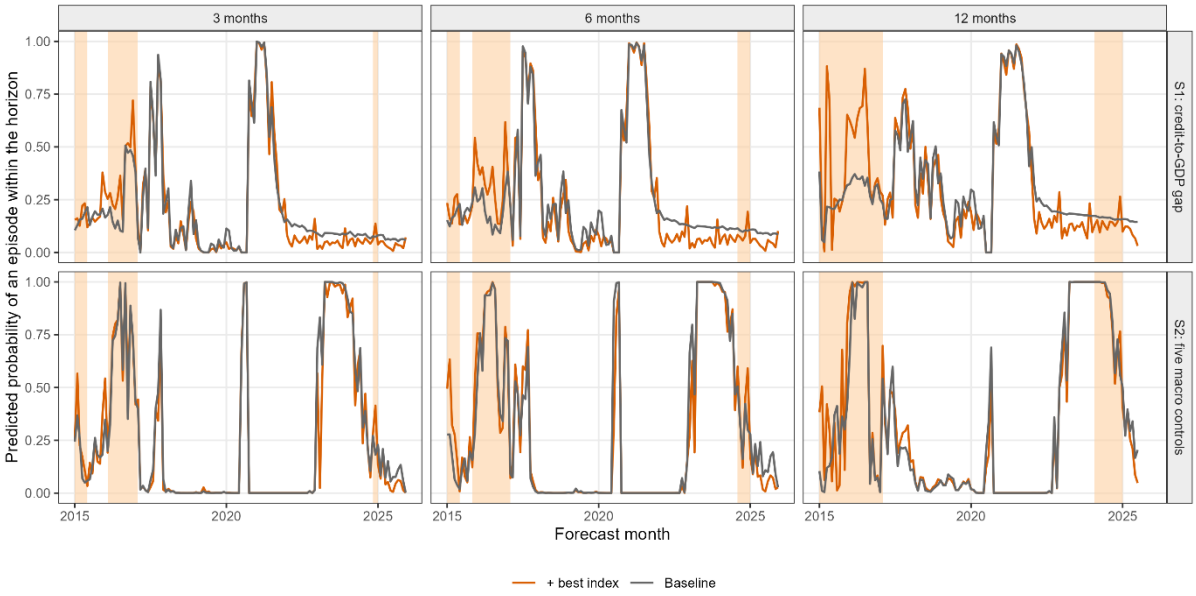
Table 7: Final segment (last 36 months): out-of-sample AUROC, by information set

			S0: no controls		S1: credit-to-GDP gap					S2: five macro controls				
Outcome	Months	N (events)	Index	BEWI alone	Index	Gap	+ BEWI	p	q	Index	Macro	+ BEWI	p	q
Deposits (collapse)	3	30 (18)	Sha	0.569	Sha	0.307†	0.529	0.037	0.099	Sha	0.745	0.760	0.707	0.808
	6	30 (23)	Sha	0.377†	Sha	0.329†	0.338	0.818	0.818	Sha	0.702	0.656	0.552	0.808
Household credit bust	6	26 (6)	Dis	0.775	Dis	0.358†	0.750	0.007	0.042	Dis	0.383†	0.408	0.414	0.808
	12	20 (12)	Dis	0.698	Dis	0.219†	0.688	0.011	0.042	Dis	0.323†	0.344	0.403	0.808
House price bust	3	27 (10)	Dem	0.153†	Dis	0.900	0.671	0.102	0.204	Dis	0.482†	0.500	0.693	0.808
	6	24 (10)	Dem	0.021†	Dis	0.414†	0.579	0.229	0.302	Dem	0.264†	0.250	0.480	0.808
	12	18 (10)	Dem	0.150†	Dis	0.562	0.750	0.264	0.302	Dis	0.012†	0.000	0.480	0.808

Notes: Final segment: the same real-time forecasts as Table 6, for the last 36 months of the data (August 2023 onwards; the search indices end in December 2025, so the segment holds about 30 forecast months at 3 months ahead and fewer at longer horizons); nothing is re-estimated. In each cell the BEWI index (Dem, Dis, Sha) is the one with the highest AUROC on the forecasts before the final segment only, and the final segment is evaluated once. N (events) = months forecast in the segment (S2 sample) and months labelled as events. Only cells with at least five events and at least five non-events are shown; Impaired advances and all three boom outcomes have no events in this window, and mortgage credit busts have one, so they cannot be scored. p = DeLong test of + BEWI against the baseline on the same origins; stars are not shown; q = Benjamini–Hochberg q-value over all final-segment tests of the information set, including cells not shown. † = baseline AUROC below 0.5 (S0: BEWI alone not above 0.5), not interpreted. With so few events in the segment, all values are imprecise.

The Distress index sharpens the household credit bust forecasts of the credit-to-GDP gap but changes those of the five controls very little (Figure 3). Figure 3 shows the forecast probabilities with and without the Distress index, the best index at 3, 6 and 12 months in both information sets (Table 6). Against the gap alone the index raises the probability ahead of the shaded periods of 2015–17 and lowers it in the quiet years after 2022; against the five controls the two sets of forecasts are almost identical, consistent with the small gain in Table 6. Both baselines give a high probability in 2020–21, when no episode followed, and the five-control model stays at or near one through 2023 and early 2024, about a year before the episode that began in early 2025.

Figure 3: Household credit bust: forecast probabilities with and without the Distress index



Notes: Household credit bust: real-time forecast probabilities with and without the best index (Distress at 3, 6 and 12 months in both information sets, Table 6), by baseline (S1: credit-to-GDP gap; S2: five macro controls). Shaded: months from which an episode did start within the horizon (the realised outcome).

3.4 Robustness and sensitivity

The main results are re-estimated under alternative choices. Each exercise reruns the real-time forecasts for three outcomes: the household credit bust, which carries the main result, deposit collapses and house price booms, at 3, 6 and 12 months, against the credit-to-GDP gap (S1) and the five controls (S2). Tables report the change in AUROC when the index chosen in the main run is added to the baseline. * = the index improves the baseline on both the DeLong and the Clark–West test ($p < 0.05$); ‡ = it is significantly worse on the DeLong test; † = the baseline AUROC is below 0.5, so the comparison is not interpreted. The evaluation restrictions cover the household credit bust only.

3.4.1 Pooling the indices

The household credit bust gain does not depend on choosing the best index. Table 8 and Figure 4 replace the best single index by the equal-weight composite of the three (i.e. no choice of index), and compare it with the monthly macro model and with the credit-to-GDP gap. The composite improves on the baseline on both the DeLong and the Clark–West test in seven of 56 cells (marked with an * in Table 8), four of them with a baseline above 0.5: the household credit bust at 3 months (both baselines) and at 6 months (gap), and the mortgage credit bust at 12 months (gap). Against the monthly macro model, which has an AUROC of only 0.543 for the household credit bust at 3 months, the composite adds 0.116. After the multiple-testing adjustment the DeLong q-values of these cells are below 0.04, but their Clark–West q-values are 0.18 or higher.

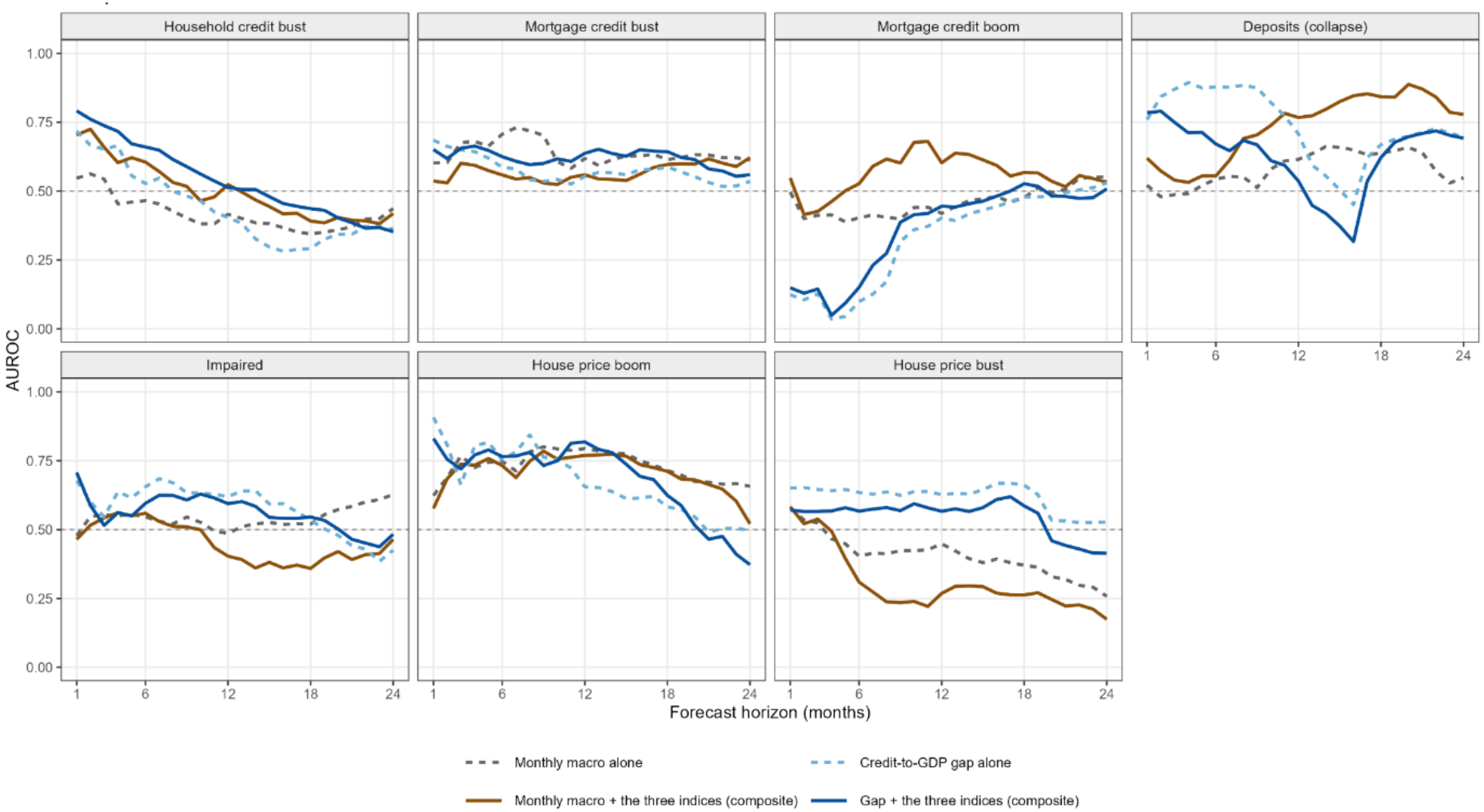
Table 8: What the all-three composite adds to the baselines: change in AUROC

Outcome	Baseline	3 months	6 months	12 months	24 months
Household credit bust	Monthly macro	**+0.116***	**+0.140*†**	**+0.108*†**	−0.018†
	Credit-to-GDP gap	**+0.086***	**+0.133***	+0.109†	−0.011†
Mortgage credit bust	Monthly macro	−0.075	−0.148	−0.059	+0.008
	Credit-to-GDP gap	+0.006	+0.039	**+0.083***	+0.024
Mortgage credit boom	Monthly macro	−0.004†	+0.097†	**+0.145*†**	−0.035
	Credit-to-GDP gap	−0.020†	+0.036†	+0.033†	−0.019
Deposits (collapse)	Monthly macro	+0.053†	+0.012	+0.152	+0.230
	Credit-to-GDP gap	−0.120‡	−0.207‡	−0.171‡	−0.004
Impaired	Monthly macro	−0.010	+0.013	−0.083†‡	−0.163‡
	Credit-to-GDP gap	−0.030	−0.060‡	−0.026	+0.058†
House price boom	Monthly macro	−0.030	−0.015	−0.025	−0.136
	Credit-to-GDP gap	+0.058	+0.012	+0.163	−0.125†‡
House price bust	Monthly macro	+0.014	−0.094†	−0.180†‡	−0.084†‡
	Credit-to-GDP gap	−0.080‡	−0.068‡	−0.060‡	−0.114‡

Notes: Δ AUROC = AUROC of baseline + composite minus AUROC of the baseline alone, on the same forecast origins (real-time recursive Firth logit; first forecast Jan 2015). The composite is the equal-weight mean of the three real-time indices. Monthly macro baseline = change in the repo rate, change in CPI inflation, growth of the leading indicator; Gap baseline = credit-to-GDP gap. * = the composite is better on both tests (paired DeLong test of the AUROCs and Clark–West test on the Brier loss, each $p < 0.05$, unadjusted). † = the baseline alone has an AUROC below 0.5. ‡ = the composite is significantly worse on the DeLong test ($p < 0.05$). Overlapping monthly labels make both p-values smaller than they should be. 7 of 56 cells pass both tests, 4 of them with a baseline above 0.5. After the Benjamini–Hochberg correction (Table A2; within each baseline over all outcomes, additions and horizons) the DeLong q-values of those 7 cells are all below 0.04, but their Clark–West q-values are 0.18 or higher.

Figure 4 shows the same comparison at every horizon: for the household credit bust the composite helps at short horizons. After the multiple-testing adjustment the DeLong q-values of the seven combinations are below 0.04, but their Clark–West q-values are 0.18 or higher. The composite is significantly worse (DeLong, $p < 0.05$) in 13 combinations (‡ in Table 8), nine of them against the credit-to-GDP gap, which forecasts well for deposit collapses and house price busts.

Figure 4: Complement: what do the behavioural indices add to a macro model?



Notes: Real-time out-of-sample forecasts: event = an episode starts within the next h months. Dashed lines: the macro model alone; solid lines: the same model with the three behavioural indices added as one composite (equal-weight average of the real-time z-scores). 'Monthly macro' = repo rate, CPI and leading indicator (no credit or balance-sheet data). The distance between the lines is not tested here: Table 8 tests the increment at 3, 6, 12 and 24 months (DeLong and Clark–West; q-values in Appendix Table A2). Event counts by outcome are in Table 6; the months labelled positive come in blocks, so the number of independent episodes is much smaller.

3.4.2 Event definition, estimation and information timing

The household credit bust result survives changes to the event definition, the estimation and the information timing (Table 9, Panel A). Across the 16 variants the Distress index raises the AUROC in 86 of 96 cells, and the gain passes both tests in 45. Against the credit-to-GDP gap it raises the AUROC in 47 of 48 cells (36 pass both tests); against the five controls in 39 of 48 (9 pass both tests), with small gains, as in the main results. The gap baseline is itself below 0.5 in 28 of the 48 S1 cells, so those cells show what the index adds to a baseline that does not work. Adding the outcome's own lag to the baseline lifts baseline AUROCs to 0.76–0.88, and the index then adds significantly only against the gap at 6 months (+0.057); against the controls it is significantly worse at 12 months (−0.043). Adding PMI employment, the ZAR/USD exchange rate, the VIX and the JSE All Share Index to both baselines leaves the picture unchanged: the Distress index raises the AUROC in all six cells (+0.023 to +0.124), and against the extended gap it passes both tests at all three horizons. Against the extended five controls the gain is +0.023 to +0.030, but none of the three cells passes both tests (the weaker of the two p-values is 0.061 to 0.090).

Deposit collapses behave as in the main results (Panel B). Against the five controls, whose AUROC is below 0.5 in 24 of 48 cells, the index raises the AUROC in 42 of 48 cells; against the credit-to-GDP gap, which forecasts well, it does so in only 10 of 48. With the extended controls, deposit collapses show the same split: the Shadow index adds +0.023 to +0.065 against the five controls plus the four new ones (whose AUROC is below 0.5), and the index lowers the AUROC against the extended gap in all three cells (−0.025 to −0.111). For house price booms (Panel C) the index raises the AUROC in all 18 cells run, but only three pass both tests, and the events are few (four to seven at the main definition).

Table 9: Robustness of the gain from adding the best index: event definition, estimation and information timing

	S1: credit-to-GDP gap			**S2: five macro controls**		
Variant	3m	6m	12m	3m	6m	12m
A. Household credit bust (Distress index)						
Main run	+0.090*	+0.158*	+0.144*†	+0.027*	+0.033*	+0.017
Event definition						
85th/15th percentile	+0.113*†	+0.146*†	+0.148†	+0.014	+0.024	−0.008
80th/20th percentile	+0.122*†	+0.180*†	+0.111†	+0.003	−0.020	−0.005
95th/5th percentile	+0.095*	+0.116*	+0.193*†	+0.015	+0.030	+0.048*
Persistence: 1 month	+0.074*	+0.116*	+0.173*†	+0.032*	+0.036	−0.001
Persistence: 3 months	+0.135*†	+0.211*†	+0.140*†	+0.034*	+0.053*	+0.032
Percentile window: 96 months	+0.060*	+0.103*	+0.102*	+0.013	+0.039*	+0.014
Percentile window: expanding	+0.118*	+0.183*	+0.156*†	+0.020*	+0.036*	+0.015
Estimation						
Initial window: 48 months	+0.140*	+0.228*†	+0.110*†	+0.058*	+0.063*	+0.010
Initial window: 84 months	+0.198*†	+0.175†	+0.145†	+0.023	+0.017	+0.008
Ordinary logit instead of Firth	+0.098*	+0.178*	+0.149*†	−0.004	−0.001	−0.024
Baseline also holds the outcome's own lag	+0.003	+0.057*	−0.036	−0.015	+0.002	−0.043‡
Information timing						
Controls with no publication lag	+0.084*	+0.134*	+0.198*†	+0.027	+0.024	+0.008
Publication lags one month longer	+0.044	+0.087*	+0.104*†	+0.014	+0.013	+0.016
Gap smoothing λ = 400,000	+0.135*	+0.157†	+0.177*†	+0.016	+0.017	+0.004
Gap smoothing λ = 2,073,600	+0.142†	+0.159†	+0.128*†	+0.014	+0.011	+0.007
Gap smoothing λ = 32,400,000	+0.138†	+0.159†	+0.121*†	+0.012	+0.012	+0.008
Additional controls						
PMI employment, ZAR/USD, VIX and JSE added to the baseline	+0.051*	+0.112*	+0.124*†	+0.023	+0.030	+0.030
B. Deposit collapses (index as in the main run)						
Main run	−0.070	−0.119‡	−0.038‡	+0.078*†	+0.060*†	+0.024†
Event definition						
85th/15th percentile	+0.019	+0.056	+0.004	+0.004	+0.028	+0.004
80th/20th percentile	+0.178*†	+0.271*†	+0.111	+0.003†	+0.012	+0.000
95th/5th percentile	−0.092	−0.134‡	−0.044‡†	+0.026	+0.044	−0.004†
Persistence: 1 month	−0.046	−0.050	−0.084‡	+0.036	+0.047	+0.022
Persistence: 3 months	−0.024	−0.090‡	−0.080‡	+0.011	+0.024†	−0.015†
Percentile window: 96 months	−0.002	−0.009	−0.016	+0.024	+0.009	+0.003
Percentile window: expanding	−0.060	−0.153‡	−0.056‡	+0.018	+0.047	+0.014†
Estimation						
Initial window: 48 months	−0.094‡	−0.145‡	−0.022	+0.076*†	+0.057*†	+0.023†
Initial window: 84 months	−0.051	−0.084‡	−0.009	+0.073*	+0.059*†	+0.019†
Ordinary logit instead of Firth	+0.008	+0.005	−0.002	+0.030*	+0.018*	−0.214‡
Baseline also holds the outcome's own lag	−0.054	−0.100‡	+0.014	+0.039	+0.039*	+0.008†
Information timing						
Controls with no publication lag	−0.043	−0.103‡	−0.031	+0.094*†	+0.043†	+0.041†
Publication lags one month longer	−0.054	−0.110‡	−0.122‡	+0.103*†	+0.079*†	+0.041†
Gap smoothing λ = 400,000	−0.074	−0.086‡	+0.042†	+0.084*†	+0.052*†	+0.045†
Gap smoothing λ = 2,073,600	−0.052	−0.087‡	−0.010	+0.083*†	+0.067*†	−0.047
Gap smoothing λ = 32,400,000	−0.061	−0.078‡	−0.057‡	+0.080*†	+0.081*†	−0.070
Additional controls						

	S1: credit-to-GDP gap			S2: five macro controls		
Variant	3m	6m	12m	3m	6m	12m
PMI employment, ZAR/USD, VIX and JSE added to the baseline	−0.100	−0.111‡	−0.025	+0.065†	+0.039†	+0.023†
C. House price boom (index as in the main run)						
Main run	+0.250	+0.138	+0.258	+0.036*	+0.107	+0.080
Event definition						
85th/15th percentile	+0.185*	+0.072	+0.183	+0.065	+0.024	+0.049†
80th/20th percentile	+0.172*	+0.062	+0.175†	+0.069	+0.001†	+0.052†
Additional controls						
PMI employment, ZAR/USD, VIX and JSE added to the baseline	+0.183*	+0.145	+0.207	+0.073	+0.080	+0.049

Notes: Each cell is the change in AUROC when the index chosen in the main run (Distress for the household credit bust; Distress, Shadow or Demand, as in Table 6) is added to the baseline, with the model re-estimated in real time under the variant in the row (first forecast January 2015; S1 = credit-to-GDP gap; S2 = five macro controls). Event definition: the 90th/10th percentile, persistence of two months and a 132-month percentile window are varied one at a time. Estimation: the initial window (60 months in the main run), the Firth estimator and the baseline specification are varied; the own-lag variant adds the outcome's own value, lagged by its publication delay, to both baselines. Information timing: the publication lags of the controls and the smoothing parameter of the credit-to-GDP gap are varied. * = better on both the DeLong and the Clark–West test ($p < 0.05$); ‡ = significantly worse on the DeLong test ($p < 0.05$); † = baseline AUROC below 0.5, not interpreted. Overlapping monthly labels make both p-values smaller than they should be. n/r = variant not run for this outcome.

3.4.3 Placebo

Shifting the indices in time by 48, 96 or 144 months removes the gains (Table 10). Across the 36 placebo cells for the household credit bust and deposit collapses, the largest gain is +0.052 and none is significant on the DeLong test. For the household credit bust the shifted Distress index changes the AUROC by −0.140 to +0.042 against the gap and by −0.023 to +0.024 against the controls, compared with +0.090 to +0.158 and +0.017 to +0.033 in the main run.

Table 10: Placebo: indices shifted in time

	S1: credit-to-GDP gap			S2: five macro controls		
Indices	3m	6m	12m	3m	6m	12m
A. Household credit bust						
Main run (not shifted)	**+0.090***	**+0.158***	**+0.144*†**	**+0.027***	**+0.033***	**+0.017**
Shifted by 48 months	−0.049	−0.140‡	−0.018†	+0.024	−0.022	−0.010
Shifted by 96 months	−0.013	+0.031	+0.042†	+0.006	−0.013	+0.016
Shifted by 144 months	−0.038	−0.011	+0.013†	−0.023	+0.004	−0.014
B. Deposit collapses						
Main run (not shifted)	**−0.070**	**−0.119‡**	**−0.038‡**	**+0.078*†**	**+0.060*†**	**+0.024†**
Shifted by 48 months	−0.087‡	−0.042‡	−0.051	−0.039†	+0.002†	−0.012†
Shifted by 96 months	−0.165‡	−0.205‡	−0.110‡	−0.010†	−0.002†	+0.052†
Shifted by 144 months	−0.048	−0.048	−0.098‡	+0.013†	+0.018†	+0.012†

Notes: The three real-time indices are shifted by 48, 96 or 144 months, which removes any predictive content, and the main-run index is added to the baseline (same cells as Table 9). Entries are the change in AUROC. * = better on both tests ($p < 0.05$); ‡ = significantly worse on the DeLong test; † = baseline AUROC below 0.5.

3.4.4 Sub-indices and leave-one-out

Against the credit-to-GDP gap, the household credit bust gain is carried by the Distress sub-indices, with mortgage default and debt resolution close to the full index, and at 6 and 12 months by the Demand sub-index for affordability searches; housing attention and credit intent add little, and the Shadow index adds nothing (Table 11). Against the controls the full Distress index is significant at 3 and 6 months, and one Distress sub-index at 6 and 12 months (credit management and debt resolution), so no single channel carries the result. The Distress result does not depend on any one search term: dropping each of the 18 terms in turn leaves the gain over the gap at +0.078 to +0.099 at 3 months and +0.138 to +0.168 at 6 months, and over the controls at +0.016 to +0.039 and +0.027 to +0.048. For deposit collapses, dropping any one of the six Shadow terms leaves the picture unchanged: the gain over the five controls stays positive (+0.021 to +0.098 at 3 months, +0.009 to +0.077 at 6 months) and the change against the gap stays negative.

Table 11: Household credit bust: sub-indices added to the baseline

	S1: credit-to-GDP gap			**S2: five macro controls**		
Index added to the baseline	3m	6m	12m	3m	6m	12m
Demand index	+0.014	+0.094*	+0.099*†	+0.019	−0.008	−0.006
Affordability searches	+0.052	+0.124*	+0.150*†	+0.023	+0.010	+0.028
Housing attention	−0.029	+0.069	+0.056†	−0.012	−0.012	−0.018
Credit intent	+0.015	+0.031	+0.037†	+0.006	−0.002	−0.005
Distress index	+0.090*	+0.158*	+0.144*†	+0.027*	+0.033*	+0.017
Mortgage default	+0.087*	+0.124*	+0.099†	+0.026	+0.018	+0.007
Credit management	+0.043	+0.109	+0.071†	+0.032	+0.035*	+0.009
Debt resolution	+0.083	+0.143*	+0.124†	+0.004	+0.014	+0.039*
Shadow index	−0.078	−0.037	−0.028†	−0.036‡	−0.016	+0.008

Notes: Change in AUROC when the index or sub-index in the row is added to the baseline, household credit bust. Demand sub-indices: affordability searches, housing attention, credit intent; Distress sub-indices: mortgage default, credit management, debt resolution. * = better on both tests ($p < 0.05$); ‡ = significantly worse on the DeLong test; † = baseline AUROC below 0.5.

3.4.5 Evaluation restrictions

Restricting the evaluation sample does not remove the household credit bust gain over the credit-to-GDP gap (Table 12). Without origins at which an episode is already under way, without the following 12 months as well, or without the COVID months, the gain over the gap has $p \leq 0.050$ in all twelve cells ($p = 0.050$ at 3 months once the 12 months after an episode are also dropped). The gain over the five controls is less secure: it holds without the COVID months at 3 and 6 months ($p = 0.032$ and 0.020), but is not significant once ongoing episodes are dropped ($p = 0.053$ at best). These restricted samples contain few events (3 to 22), and the

gap baseline falls below 0.5 in several of them, so the comparison with the gap should be read with the † marks.

Table 12: Household credit bust: AUROC under restricted evaluation samples

		All forecast months			**No ongoing episodes**			**Also no 12 months after**			**No COVID months**		
Baseline	Months	Base	+ BEWI	p	Base	+ BEWI	p	Base	+ BEWI	p	Base	+ BEWI	p
S1: gap	3	0.652	0.742	0.003	0.538	0.674	0.008	0.363†	0.599	0.050	0.717	0.824	0.003
S2: controls	3	0.776	0.802	0.036	0.766	0.782	0.353	0.734	0.753	0.376	0.749	0.783	0.032
S1: gap	6	0.528	0.686	<0.001	0.497†	0.644	0.001	0.273†	0.538	0.002	0.578	0.777	<0.001
S2: controls	6	0.746	0.780	0.006	0.762	0.786	0.053	0.733	0.759	0.121	0.711	0.744	0.020
S1: gap	12	0.404†	0.548	<0.001	0.342†	0.493	<0.001	0.167†	0.350	0.003	0.447†	0.626	<0.001
S2: controls	12	0.764	0.781	0.441	0.852	0.831	0.420	0.865	0.872	0.175	0.701	0.719	0.524

Notes: The stored real-time forecasts are re-evaluated on restricted sets of forecast origins; nothing is re-estimated. Base = baseline AUROC; + BEWI = baseline plus the Distress index; p = DeLong test of + BEWI against the baseline on the same origins. No ongoing episodes: origins at which an episode is already under way are dropped; also no 12 months after: the 12 months after an episode are dropped as well; no COVID: March 2020 to December 2021 dropped. Months forecast (events): all 132 (22), 129 (28), 123 (38); no ongoing 114 (7), 111 (13), 105 (22); also no 12 months after 92 (3), 89 (6), 83 (12); no COVID 110 (22), 107 (28), 101 (38) at 3, 6 and 12 months. † = baseline AUROC below 0.5, not interpreted.

3.4.6 Bootstrap

The DeLong test treats overlapping monthly forecasts as independent, but the labelled months come in one to three separate runs per cell. A moving-block bootstrap of the stored forecasts (blocks of 6, 12 and 24 months, 2,000 replications) gives intervals that respect this dependence. The gain from adding the Distress index to the credit-to-GDP gap for the household credit bust has a 95% interval that excludes zero at 3, 6 and 12 months for all three block lengths (with 12-month blocks, +0.090 [+0.030, +0.265], +0.158 [+0.062, +0.303] and +0.144 [+0.061, +0.241]). Against the five controls the intervals include zero (+0.027 [−0.001, +0.048] at 3 months), as in the small gains above. On its own, the Demand index has an AUROC above 0.5 for the household credit bust at 3 and 6 months (0.642 and 0.685) and the Shadow index for deposit collapses at all four horizons (0.867 to 0.943); the interval for the Distress index alone includes 0.5 at 3 and 6 months. For the house price boom the interval excludes zero only for the gain over the gap at 12 months. With so few separate episodes, these intervals are indicative.

4 Conclusion

This paper examines whether online search behaviour can enhance macroprudential surveillance by providing earlier signals of emerging financial vulnerabilities. Using Google Trends data for South Africa, behavioural early warning indicators are constructed that capture housing and mortgage demand, formal financial distress and informal credit substitution. Their predictive content is evaluated in quasi-real-time recursive out-of-sample forecasts for seven banking, credit and housing outcomes at horizons of up to 24 months.

The results show that search behaviour carries a real-time signal on its own and provides statistically significant incremental predictive information beyond established macro-financial indicators. The channels differ: the housing and mortgage demand and formal financial distress indices lead household credit busts by up to 10 and 8 months, the informal-credit Shadow index leads deposit collapses by up to 12 months, and the formal financial distress index leads house price booms by up to 13 months.

From a policy perspective, the results suggest that behavioural search data can complement existing macroprudential surveillance frameworks by providing timely information that is not readily observable in official statistics. This is particularly relevant in emerging market economies, where publication lags and limited information on informal credit markets may delay the identification of emerging vulnerabilities. Because Google Trends data are freely available and published at high frequency, they offer central banks and supervisory authorities a practical and low-cost addition to existing early warning systems.

Although the analysis focuses on South Africa, the proposed behavioural taxonomy provides a framework that can be adapted to other countries by tailoring search terms to local institutional and financial conditions. Future research could evaluate the performance of these indicators across countries, combine behavioural measures with alternative digital data sources, and assess their usefulness within more flexible forecasting frameworks.

References

1. Aldasoro, I., Borio, C., and Drehmann, M. 2018. Early warning indicators of banking crises: Expanding the family. *BIS Quarterly Review,* March. URL: https://www.bis.org/publ/qtrpdf/r_qt1803e.pdf

2. Alessandri, P., Bologna, P., and Galardo, M. 2022. Financial crises, macroprudential policy and the reliability of credit-to-GDP gaps. *IMF Economic Reviews,* 70: 625-667. DOI: https://doi.org/10.1057/s41308-022-00168-6

3. Alessi, L. and Detken, C. 2011. Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy,* 27(3): 520-533. DOI: https://doi.org/10.1016/j.ejpoleco.2011.01.003

4. Basel Committee on Banking Supervision, 2010. Guidance for national authorities operating the countercyclical capital buffer. Bank for International Settlements, December. URL: https://www.bis.org/publ/bcbs187.htm

5. Bełej, M. 2023. Predicting housing price trends in Poland: Online social engagement - Google Trends. *Real Estate Management and Valuation,* 31(4), 73-87. DOI: https://doi.org/10.2478/remav-2023-0032

6. Benjamini, Y. and Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1): 289-300. DOI: https://doi.org/10.1111/j.2517-6161.1995.Tb02031.x

7. Beracha, E., and Wintoki, M.B., 2013. Forecasting Residential Real Estate Price Changes from Online Search Activity, *Journal of Real Estate Research*, 35: (3): 283-312, DOI: https://doi.org/10.1080/10835547.2013.12091364

8. Borio, C.E. 2003. Towards a Macroprudential Framework for Financial Supervision and Regulation?, *CESifo Economic Studies*, 49(2): 181-215 DOI: https://doi.org/10.1093/cesifo/49.2.181

9. Borio, C.E. and Drehmann, M., 2009. Assessing the risk of banking crises - revisited. *BIS Quarterly Review, March*. [Online]. Available: https://www.bis.org/publ/qtrpdf/r_qt0903e.htm

10. Bulczak, G.M. 2021. Use of Google Trends to predict the real estate market: Evidence from the United Kingdom. *International Real Estate Review,* 24(4): 613-631. DOI: https://doi.org/10.53383/100332

11. Burra, P., de Jongh, P.J., Raubenheimer, H., van Vuuren, G., and Wild, H. 2015. Implementing the countercyclical capital buffer in South Africa: Practical considerations. *South African Journal of Economics and Management Sciences,* 18(1): 105-123. DOI: https://doi.org/10.4102/sajems.v18i1.956

12. Case, K.E., and Shiller, R.J. 2003. IS there a bubble in the housing market? *Brookings Papers on Economic Activity,* 34(2): 299-362. URL: https://www.jstor.org/stable/1209196

13. 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

14. Claessens, S., Kose, M.A., and Terrones, M.E. 2012. How do business and financial cycles interact? *Journal of International Economics,*87(1): 178-190. DOI: https://doi.org/10.1016/j.jinteco.2011.11.008

15. Clark, T.E. and West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1): 291-311. DOI: https://doi.org/10.1016/j.jeconom.2006.05.023

16. DeLong, E.R., DeLong, D.M. and Clarke-Pearson, D.L., 1988. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics, 44(3): 837-845. DOI: https://doi.org/10.2307/2531595

17. Dierick, F., Point, E., Cornacchia, W. and, Pirovano, M. 2016. *Closing Real Estate Data Gaps for financial stability monitoring and macroprudential policy in the EU. Bank for International Settlements, IFC-National Bank of Belgium Workshop on Data needs and Statistics compilation for macroprudential analysis,* 18-19 May, Brussels: Belgium, [Online]. Available: https://www.bis.org/ifc/publ/ifcb46f.pdf

18. Dietzel, M.A. 2016. Sentiment-based predictions of housing market turning points with Google Trends. *International Journal of Housing Markets and Analysis,* 9(1): 108-136. DOI: https://doi.org/10.1108/IJHMA-12-2014-0058

19. Drehmann, M., and Juselius, M. 2014. Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting,* 30(3): 759-780. DOI: https://doi.org/10.1016/j.ijforecast.2013.10.002

20. Edge, R.E., and Meisenzahl, R.R. 2011. The unreliability of credit-to-GDP ratio gaps in real time: Implications for countercyclical capital buffers. *International Journal of Central Banking,* 7(4): 261-298. DOI: https://dx.doi.org/10.2139/ssrn.1956719

21. Ferrari, S., Pirovano, M., and Cornacchia, W. 2015. Identifying early warning indicators for real estate-related banking crises. European Systemic Risk Board Occasional Paper Series, 2015/08. [Online]. Available: https://www.esrb.europa.eu/pub/pdf/occasional/20150827_occasional_paper_8.pdf?ad918a6c476f04ae5d00ab18564294bd

22. Firth, D. 1993. Bias reduction of maximum likelihood estimates. *Biometrika,* 80(1): 27-38. DOI: https://doi.org/10.1093/biomet/80.1.27

23. Friedman, M., 1948. A monetary and fiscal framework for economic stability, *American Economic Review,* 38: 245-264. URL: https://www.jstor.org/stable/1810624

24. Hagemann, D., and Wohlmann, M. 2019. An early warning system to identify house price bubbles. *Journal of European Real Estate Research,* 12(3): 291-310. DOI: https://doi.org/10.1108/JERER-03-2019-0006

25. Hanson, S.G., Kashyap, A.K. and Stein, J.C. 2011. A Macroprudential Approach to Financial Regulation. *Journal of Economic Perspectives* 25 (1): 3–28**.** DOI: https://doi.org/10.1257/jep.25.1.3

26. Heinze, G., and Schemper, M. 2002. A solution to the problem of separation in logistic regression. *Statistica in Medicine,* 21(16): 2409-2419. DOI: https://doi.org/10.1002/sim.1047

27. Kaminsky, G., Lizondo, S., and Reinhart, C.M. 1998. Leading indicators of currency crises. *IMF Economic Review,* 45:1-48. DOI: https://doi.org/10.2307/3867328

28. Kaplan, G., Mitman, K., and Violante, G.L. 2020. The housing boom and bust: Model meets evidence. *Journal of Political Economy,* 128(9): 3285-3345. https://doi.org/10.1086/708816

29. Kawata, H., Kurachi, Y., Nakamura, K., and Teranishi, Y. 2013. Impact of macroprudential policy measures on economic dynamics: Simulation using a financial macro-econometric model. Bank of Japan Working Paper Series. Available: https://www.rbnz.govt.nz/-/media/project/sites/rbnz/files/events/22oct2014/presentations/5960189.pdf

30. 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

31. Kwon, Y. and Park, S.Y. 2023. Modeling an early warning system for household debt risk in Korea. *Journal of Asian Economics,* 81: 101574. DOI: https://doi.org/10.1016/j.asieco.2022.101574

32. Lazer, D., Kennedy, R., King, G. and Vespignani, A., 2014. The parable of Google Flu: traps in big data analysis. *Science*, 343(6176): 1203-1205. DOI: https://doi.org/10.1126/science.1248506

33. Lo Duca, M., and Peltonen, T.A. 2013. Assessing systemic risks and predicting systemic events. *Journal of Banking and Finance.* 37(7): 2183-2195. DOI: https://doi.org/10.1016/j.jbankfin.2012.06.010

34. 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

35. Msiska, W., Sikhosana, A., and Vermeulen, C. 2026. The credit gap as a real-time early warning indicator of financial imbalances: A South African perspective. South African Reserve Bank Working Paper Series, WP/26/04. [Online]. Available: https://www.resbank.co.za/content/dam/sarb/publications/working-papers/2026/26-04/credit-gap.pdf

36. Newey, W.K. and West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review*, *28*(3): 777-787. DOI: https://doi.org/10.2307/2526578

37. Orphanides, A., and van Norden, S. 2002. The unreliability of output-gap estimates in real time. *The Review of Economics and Statistics*, 84(4): 569-583. DOI: https://doi.org/10.1162/003465302760556422

38. 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

39. South African Reserve Bank (SARB), 2026. Online Statistical Query: historical macroeconomic timeseries information. Pretoria: SARB. Available: https://www.resbank.co.za/en/home/what-we-do/statistics/releases/online-statistical-query

40. Statistics South Africa, 2026a. Consumer Price Index, July 2026 (Statistical release P0141). Pretoria: Statistics South Africa. Available: https://www.statssa.gov.za/publications/P0141/CPIHistory.pdf.

41. Statistics South Africa, 2026b. Residential Property Price Index, February 2026 (Statistical release P0160). Pretoria: Statistics South Africa. Available: https://www.statssa.gov.za/timeseriesdata/Excel/P0160%20Residential%20Property%20Price%20Index%20Report(202605).zip

42. Statistics South Africa, 2026c. Gross Domestic Product, 2026Q2 (Statistical release P0441). Pretoria: Statistics South Africa. Available: https://www.statssa.gov.za/publications/P0441/GDP%20P0441%20-%20GDP%20Time%20series%20Q2%202026.xlsx

43. 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

44. 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

45. 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

46. World Bank. 2026. Individuals using the Internet (% of population) – South Africa. [Online]. Available: https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=ZA

47. Wu, L., and Brynjolfsson, E. The future of prediction: How Google searches foreshadow housing prices and quantities. 2009. *ICIS 2009 Proceedings,* 147. URL: http://aisel.aisnet.org/icis2009/147.

Appendix

Table A1: Stand-alone AUROC of each indicator, by horizon: the other outcomes

Indicator	Impaired				Mortgage credit boom			
	3 months	**6 months**	**12 months**	**24 months**	**3 months**	**6 months**	**12 months**	**24 months**
A. On their own								
Credit-to-GDP gap	0.546	**0.656***	**0.620***	0.425	0.127	0.099	0.402	0.530
Demand index	**0.614**	0.579	0.614*	0.588	0.412	0.418	0.547	0.519
Distress index	0.570	0.525	0.569	0.578	0.239	0.235	0.431	0.555
Shadow index	0.581	0.484	0.565	**0.605**	0.589	0.592	0.477	0.516
Five macro controls	0.569	0.498	0.441	0.398	**0.670***	**0.683***	**0.582**	**0.697***
B. Gap and indices								
Gap alone	0.546	**0.656***	0.620*	0.425	0.127	0.099	0.402	0.530
Gap + Demand	**0.573**	0.604	0.607*	0.464	0.308	0.367	**0.527**	**0.626***
Gap + Distress	0.515	0.630*	0.585	**0.476**	0.109	0.125	0.441	0.620*
Gap + Shadow	0.551	0.583	**0.647***	0.297	0.297	0.345	0.438	0.533
Gap + all three	0.501	0.511	0.605*	0.282	**0.437**	**0.455**	0.459	0.613
C. Controls and indices								
Controls alone	0.569	0.498	0.441	0.398	**0.670***	**0.683***	0.582	0.697*
Controls + Demand	**0.573**	**0.524**	0.440	0.397	0.588	0.664*	**0.617***	0.717*
Controls + Distress	0.564	0.516	0.448	**0.404**	0.549	0.672*	0.602	**0.718***
Controls + Shadow	0.536	0.459	0.455	0.384	0.668*	0.663*	0.546	0.673*
Controls + all three	0.525	0.464	**0.460**	0.386	0.594	0.654*	0.587	0.699*
Origins (events)	*127 (27)*	*124 (39)*	*118 (57)*	*106 (84)*	*113 (18)*	*110 (22)*	*104 (28)*	*92 (40)*

Table A1 (continued)

Indicator	Mortgage credit bust				House price boom			
	3 months	**6 months**	**12 months**	**24 months**	**3 months**	**6 months**	**12 months**	**24 months**
A. On their own								
Credit-to-GDP gap	0.650	0.586	0.554	0.535	0.663	0.754*	0.655	0.497
Demand index	**0.758***	**0.634***	**0.688***	**0.685***	0.692	0.742	0.736	0.315
Distress index	0.553	0.490	0.552	0.570	**0.897***	**0.893***	**0.828***	0.112
Shadow index	0.716*	0.599	0.553	0.640*	0.687*	0.686*	0.679*	**0.721***
Five macro controls	0.599	0.508	0.440	0.602	0.879*	0.682	0.595	0.473
B. Gap and indices								
Gap alone	0.650	0.586	0.554	0.535	0.663	0.754*	0.655	0.497
Gap + Demand	0.653	0.592	0.534	0.516	0.704	0.754*	0.811*	0.427
Gap + Distress	0.622	0.577	0.536	0.499	0.913*	**0.892***	**0.914***	0.409
Gap + Shadow	**0.711***	0.625	0.608	**0.563**	0.597	0.648*	0.635	**0.664**
Gap + all three	0.614	**0.631**	**0.640***	0.457	**0.923***	0.875*	0.797*	0.577
C. Controls and indices								
Controls alone	0.599	0.508	0.440	0.602	0.879*	0.682	0.595	0.473
Controls + Demand	**0.608**	0.510	**0.443**	0.619*	0.796*	0.686	0.561	0.408
Controls + Distress	0.574	0.499	0.434	0.615*	**0.915***	0.786*	**0.675***	0.311
Controls + Shadow	0.607	0.518	0.426	0.626*	0.883*	0.789*	0.632	**0.604**
Controls + all three	0.573	**0.523**	0.432	**0.639***	0.911*	**0.818***	0.583	0.472
Origins (events)	*126 (14)*	*123 (18)*	*117 (30)*	*105 (52)*	*130 (4)*	*127 (7)*	*121 (7)*	*109 (7)*

Table A1 (continued)

Indicator	House price bust							
	3 months	6 months	12 months	24 months	3 months	6 months	12 months	24 months
A. On their own								
Credit-to-GDP gap	**0.646***	**0.635***	**0.627***	**0.528**				
Demand index	0.382	0.363	0.389	0.408				
Distress index	0.464	0.395	0.379	0.349				
Shadow index	0.316	0.360	0.398	0.487				
Five macro controls	0.572	0.451	0.220	0.318				
B. Gap and indices								
Gap alone	**0.646***	0.635*	0.627*	**0.528**				
Gap + Demand	0.538	0.512	0.537	0.456				
Gap + Distress	0.639*	**0.638***	**0.648***	0.524				
Gap + Shadow	0.473	0.451	0.442	0.408				
Gap + all three	0.470	0.441	0.433	0.410				
C. Controls and indices								
Controls alone	0.572	0.451	**0.220**	0.318				
Controls + Demand	**0.594**	**0.470**	0.193	0.284				
Controls + Distress	0.592	0.465	0.203	0.274				
Controls + Shadow	0.497	0.354	0.101	**0.351**				
Controls + all three	0.515	0.387	0.114	0.345				
Origins (events)	*130 (28)*	*127 (34)*	*121 (46)*	*113 (68)*				

Notes: Each cell is the AUROC of the indicator at the forecast horizon in the column head (real-time recursive Firth logit, first forecast Jan 2015). The models of a panel are compared on the same forecast origins, which are also common to the no-controls constant forecast. * = the 95% DeLong interval excludes 0.5. Bold = highest AUROC of the panel at that horizon; grey = the highest or not significantly different from it (paired DeLong test, two-sided $p \geq 0.05$). Panel A: the credit-to-GDP gap (information set S1), each index on its own (S0), the five macro controls together (S2). Panel B: the gap alone and with each index and with all three. Panel C: the five controls alone and with each index and with all three. Impaired is the monthly change in the impaired-advances ratio. Household credit boom has no episode in the forecast period and is not shown. Stars are generous because overlapping monthly labels are treated as independent.

Table A2. All additions to the baselines: change in AUROC with tests

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
Household credit bust	Monthly macro	3	Composite (all three)	132 (22)	0.543	0.659	**+0.116***	0.003	0.039	0.023	0.201
			Composite (Demand + Distress)	132 (22)	0.543	0.631	**+0.088***	0.016	0.014	0.064	0.162
			Demand	132 (22)	0.543	0.590	+0.047	0.263	0.039	0.409	0.201
			Distress	132 (22)	0.543	0.637	**+0.094***	0.004	0.012	0.026	0.162
			Shadow	132 (22)	0.543	0.445	−0.098‡	0.029	0.864	0.082	0.945
Household credit bust	Monthly macro	6	Composite (all three)	129 (28)	0.465	0.605	**+0.140*†**	<0.001	0.023	0.004	0.197
			Composite (Demand + Distress)	129 (28)	0.465	0.594	**+0.128*†**	<0.001	0.002	0.002	0.162
			Demand	129 (28)	0.465	0.562	**+0.096*†**	0.008	0.006	0.036	0.162
			Distress	129 (28)	0.465	0.596	**+0.131*†**	<0.001	0.003	0.002	0.162
			Shadow	129 (28)	0.465	0.455	−0.011†	0.649	0.711	0.787	0.830
Household credit bust	Monthly macro	12	Composite (all three)	123 (38)	0.416	0.524	**+0.108*†**	0.005	0.030	0.026	0.201
			Composite (Demand + Distress)	123 (38)	0.416	0.528	**+0.113*†**	0.004	0.003	0.026	0.162
			Demand	123 (38)	0.416	0.537	**+0.121*†**	0.003	0.014	0.023	0.162
			Distress	123 (38)	0.416	0.504	**+0.089*†**	0.018	0.008	0.068	0.162
			Shadow	123 (38)	0.416	0.424	+0.008†	0.799	0.423	0.895	0.559
Household credit bust	Monthly macro	24	Composite (all three)	115 (44)	0.437	0.419	−0.018†	0.666	0.139	0.790	0.300
			Composite (Demand + Distress)	115 (44)	0.437	0.512	+0.076†	0.102	0.078	0.204	0.250
			Demand	115 (44)	0.437	0.579	**+0.142*†**	<0.001	0.009	0.004	0.162
			Distress	115 (44)	0.437	0.396	−0.041†	0.385	0.374	0.529	0.515
			Shadow	115 (44)	0.437	0.534	+0.097†	0.008	0.190	0.036	0.340

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
Household credit bust	Credit-to-GDP gap	3	Composite (all three)	132 (22)	0.652	0.738	**+0.086***	0.012	0.013	0.037	0.180
			Composite (Demand + Distress)	132 (22)	0.652	0.717	+0.065	0.048	0.055	0.098	0.242
			Demand	132 (22)	0.652	0.666	+0.014	0.706	0.173	0.783	0.403
			Distress	132 (22)	0.652	0.742	**+0.090***	0.003	0.014	0.012	0.180
			Shadow	132 (22)	0.652	0.574	−0.078	0.109	0.949	0.182	0.979
Household credit bust	Credit-to-GDP gap	6	Composite (all three)	129 (28)	0.528	0.660	**+0.133***	<0.001	0.033	0.003	0.191
			Composite (Demand + Distress)	129 (28)	0.528	0.677	**+0.149***	<0.001	0.010	0.002	0.180
			Demand	129 (28)	0.528	0.622	**+0.094***	0.029	0.036	0.068	0.191
			Distress	129 (28)	0.528	0.686	**+0.158***	<0.001	0.020	<0.001	0.180
			Shadow	129 (28)	0.528	0.490	−0.037	0.069	0.992	0.128	0.992
Household credit bust	Credit-to-GDP gap	12	Composite (all three)	123 (38)	0.404	0.513	+0.109†	<0.001	0.073	0.002	0.283
			Composite (Demand + Distress)	123 (38)	0.404	0.566	**+0.162*†**	<0.001	0.005	<0.001	0.165
			Demand	123 (38)	0.404	0.503	**+0.099*†**	0.025	0.038	0.061	0.191
			Distress	123 (38)	0.404	0.548	**+0.144*†**	<0.001	0.033	<0.001	0.191
			Shadow	123 (38)	0.404	0.376	−0.028†	0.360	0.505	0.472	0.786
Household credit bust	Credit-to-GDP gap	24	Composite (all three)	115 (44)	0.363	0.353	−0.011†	0.821	0.629	0.865	0.877
			Composite (Demand + Distress)	115 (44)	0.363	0.463	+0.100†	0.036	0.096	0.082	0.316
			Demand	115 (44)	0.363	0.569	**+0.205*†**	<0.001	0.024	<0.001	0.191
			Distress	115 (44)	0.363	0.352	−0.011†	0.822	0.671	0.865	0.895
			Shadow	115 (44)	0.363	0.344	−0.019†	0.570	0.906	0.682	0.979
Mortgage credit bust	Monthly macro	3	Composite (all three)	126 (14)	0.676	0.601	−0.075	0.573	0.375	0.730	0.515

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Composite (Demand + Distress)	126 (14)	0.676	0.619	−0.057	0.104	0.977	0.204	0.999
			Demand	126 (14)	0.676	0.661	−0.015	0.632	0.916	0.783	0.977
			Distress	126 (14)	0.676	0.533	−0.143‡	0.023	0.999	0.074	1.000
			Shadow	126 (14)	0.676	0.616	−0.060	0.652	0.235	0.787	0.387
Mortgage credit bust	Monthly macro	6	Composite (all three)	123 (18)	0.707	0.559	−0.148	0.163	0.146	0.281	0.300
			Composite (Demand + Distress)	123 (18)	0.707	0.663	−0.043	0.089	0.217	0.184	0.366
			Demand	123 (18)	0.707	0.679	−0.028	0.314	0.277	0.461	0.445
			Distress	123 (18)	0.707	0.601	−0.106‡	0.034	0.317	0.090	0.477
			Shadow	123 (18)	0.707	0.523	−0.184	0.079	0.126	0.165	0.292
Mortgage credit bust	Monthly macro	12	Composite (all three)	117 (30)	0.618	0.559	−0.059	0.509	0.087	0.672	0.256
			Composite (Demand + Distress)	117 (30)	0.618	0.734	**+0.116***	0.006	0.011	0.032	0.162
			Demand	117 (30)	0.618	0.748	**+0.130***	0.005	0.040	0.029	0.201
			Distress	117 (30)	0.618	0.675	+0.056	0.221	0.059	0.355	0.244
			Shadow	117 (30)	0.618	0.519	−0.100	0.268	0.088	0.412	0.256
Mortgage credit bust	Monthly macro	24	Composite (all three)	105 (52)	0.613	0.622	+0.008	0.903	0.413	0.939	0.550
			Composite (Demand + Distress)	105 (52)	0.613	0.701	+0.088	0.006	0.069	0.029	0.248
			Demand	105 (52)	0.613	0.735	+0.122	<0.001	0.146	0.009	0.300
			Distress	105 (52)	0.613	0.619	+0.006	0.879	0.292	0.939	0.460
			Shadow	105 (52)	0.613	0.645	+0.032	0.656	0.349	0.787	0.507
Mortgage credit bust	Credit-to-GDP gap	3	Composite (all three)	126 (14)	0.650	0.656	+0.006	0.861	0.938	0.888	0.979
			Composite (Demand + Distress)	126 (14)	0.650	0.643	−0.007	0.763	0.841	0.833	0.977

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Demand	126 (14)	0.650	0.653	+0.003	0.869	0.382	0.888	0.669
			Distress	126 (14)	0.650	0.622	−0.027	0.490	0.962	0.607	0.979
			Shadow	126 (14)	0.650	0.711	+0.061	0.026	0.257	0.062	0.522
Mortgage credit bust	Credit-to-GDP gap	6	Composite (all three)	123 (18)	0.586	0.625	+0.039	0.080	0.622	0.142	0.877
			Composite (Demand + Distress)	123 (18)	0.586	0.595	+0.009	0.636	0.797	0.723	0.962
			Demand	123 (18)	0.586	0.592	+0.006	0.767	0.468	0.833	0.753
			Distress	123 (18)	0.586	0.577	−0.010	0.606	0.932	0.710	0.979
			Shadow	123 (18)	0.586	0.625	+0.039	0.085	0.220	0.149	0.497
Mortgage credit bust	Credit-to-GDP gap	12	Composite (all three)	117 (30)	0.554	0.637	**+0.083***	<0.001	0.045	0.002	0.219
			Composite (Demand + Distress)	117 (30)	0.554	0.538	−0.016	0.272	0.427	0.377	0.720
			Demand	117 (30)	0.554	0.534	−0.020	0.172	0.692	0.265	0.906
			Distress	117 (30)	0.554	0.536	−0.018	0.144	0.613	0.226	0.877
			Shadow	117 (30)	0.554	0.608	+0.054	0.018	0.197	0.046	0.453
Mortgage credit bust	Credit-to-GDP gap	24	Composite (all three)	105 (52)	0.535	0.560	+0.024	0.255	0.453	0.361	0.746
			Composite (Demand + Distress)	105 (52)	0.535	0.503	−0.032‡	0.007	0.632	0.026	0.877
			Demand	105 (52)	0.535	0.516	−0.020‡	0.037	0.504	0.082	0.786
			Distress	105 (52)	0.535	0.499	−0.036‡	0.016	0.639	0.045	0.877
			Shadow	105 (52)	0.535	0.563	+0.028	0.615	0.313	0.710	0.600
Mortgage credit boom	Monthly macro	3	Composite (all three)	126 (18)	0.436	0.433	−0.004†	0.914	0.305	0.941	0.469
			Composite (Demand + Distress)	126 (18)	0.436	0.458	+0.022†	0.658	0.199	0.787	0.348
			Demand	126 (18)	0.436	0.465	+0.029†	0.587	0.164	0.733	0.317
			Distress	126 (18)	0.436	0.443	+0.007†	0.847	0.370	0.913	0.515

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Shadow	126 (18)	0.436	0.526	+0.090†	0.065	0.273	0.140	0.444
Mortgage credit boom	Monthly macro	6	Composite (all three)	123 (22)	0.464	0.561	+0.097†	0.035	0.130	0.090	0.292
			Composite (Demand + Distress)	123 (22)	0.464	0.568	+0.104†	0.025	0.082	0.074	0.250
			Demand	123 (22)	0.464	0.571	+0.107†	0.035	0.081	0.090	0.250
			Distress	123 (22)	0.464	0.524	+0.059†	0.130	0.164	0.237	0.317
			Shadow	123 (22)	0.464	0.593	+0.129†	0.024	0.129	0.074	0.292
Mortgage credit boom	Monthly macro	12	Composite (all three)	117 (28)	0.497	0.642	**+0.145*†**	<0.001	0.034	0.006	0.201
			Composite (Demand + Distress)	117 (28)	0.497	0.638	**+0.142*†**	<0.001	0.025	<0.001	0.197
			Demand	117 (28)	0.497	0.621	**+0.124*†**	<0.001	0.038	<0.001	0.201
			Distress	117 (28)	0.497	0.585	**+0.088*†**	0.024	0.030	0.074	0.201
			Shadow	117 (28)	0.497	0.556	+0.059†	0.208	0.144	0.342	0.300
Mortgage credit boom	Monthly macro	24	Composite (all three)	105 (40)	0.641	0.605	−0.035	0.223	0.361	0.355	0.515
			Composite (Demand + Distress)	105 (40)	0.641	0.699	+0.058	0.026	0.071	0.075	0.248
			Demand	105 (40)	0.641	0.678	+0.037	0.114	0.145	0.213	0.300
			Distress	105 (40)	0.641	0.703	+0.062	0.056	0.037	0.123	0.201
			Shadow	105 (40)	0.641	0.635	−0.006	0.833	0.300	0.905	0.467
Mortgage credit boom	Credit-to-GDP gap	3	Composite (all three)	126 (18)	0.184	0.165	−0.020†	0.505	0.959	0.612	0.979
			Composite (Demand + Distress)	126 (18)	0.184	0.140	−0.044†	0.400	0.949	0.519	0.979
			Demand	126 (18)	0.184	0.318	+0.134†	0.061	0.844	0.116	0.977
			Distress	126 (18)	0.184	0.131	−0.053†	0.311	0.965	0.414	0.979
			Shadow	126 (18)	0.184	0.302	+0.118†	0.111	0.071	0.182	0.283

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
Mortgage credit boom	Credit-to-GDP gap	6	Composite (all three)	123 (22)	0.188	0.224	+0.036†	0.109	0.911	0.182	0.979
			Composite (Demand + Distress)	123 (22)	0.188	0.292	+0.104†	0.003	0.896	0.014	0.979
			Demand	123 (22)	0.188	0.404	+0.216†	<0.001	0.795	<0.001	0.962
			Distress	123 (22)	0.188	0.206	+0.018†	0.215	0.933	0.313	0.979
			Shadow	123 (22)	0.188	0.363	**+0.175*†**	0.018	0.035	0.046	0.191
Mortgage credit boom	Credit-to-GDP gap	12	Composite (all three)	117 (28)	0.458	0.491	+0.033†	0.472	0.038	0.590	0.191
			Composite (Demand + Distress)	117 (28)	0.458	0.548	**+0.090*†**	<0.001	0.011	0.005	0.180
			Demand	117 (28)	0.458	0.565	**+0.107*†**	<0.001	0.007	0.002	0.180
			Distress	117 (28)	0.458	0.485	+0.026†	0.446	0.038	0.573	0.191
			Shadow	117 (28)	0.458	0.486	+0.027†	0.609	0.127	0.710	0.360
Mortgage credit boom	Credit-to-GDP gap	24	Composite (all three)	105 (40)	0.624	0.605	−0.019	0.643	0.166	0.726	0.401
			Composite (Demand + Distress)	105 (40)	0.624	0.701	**+0.077***	0.005	0.001	0.021	0.081
			Demand	105 (40)	0.624	0.701	**+0.077***	<0.001	<0.001	0.002	0.013
			Distress	105 (40)	0.624	0.695	**+0.070***	0.045	0.019	0.095	0.180
			Shadow	105 (40)	0.624	0.611	−0.013	0.497	0.903	0.610	0.979
Deposits (collapse)	Monthly macro	3	Composite (all three)	132 (30)	0.487	0.540	+0.053†	0.218	0.036	0.355	0.201
			Composite (Demand + Distress)	132 (30)	0.487	0.410	−0.077†‡	0.031	0.543	0.084	0.679
			Demand	132 (30)	0.487	0.408	−0.080†‡	0.020	0.746	0.072	0.857
			Distress	132 (30)	0.487	0.466	−0.021†	0.294	0.284	0.447	0.452
			Shadow	132 (30)	0.487	0.741	**+0.254*†**	<0.001	0.007	<0.001	0.162
Deposits (collapse)	Monthly macro	6	Composite (all three)	132 (38)	0.543	0.555	+0.012	0.833	0.106	0.905	0.275
			Composite (Demand + Distress)	132 (38)	0.543	0.396	−0.148‡	0.002	0.369	0.014	0.515

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Demand	132 (38)	0.543	0.405	−0.139‡	0.002	0.613	0.018	0.740
			Distress	132 (38)	0.543	0.460	−0.083‡	0.037	0.176	0.092	0.326
			Shadow	132 (38)	0.543	0.760	+0.217	<0.001	0.064	0.002	0.247
Deposits (collapse)	Monthly macro	12	Composite (all three)	127 (45)	0.615	0.767	+0.152	0.009	0.148	0.039	0.300
			Composite (Demand + Distress)	127 (45)	0.615	0.542	−0.073	0.111	0.525	0.211	0.662
			Demand	127 (45)	0.615	0.527	−0.088	0.074	0.652	0.157	0.774
			Distress	127 (45)	0.615	0.659	+0.044	0.313	0.168	0.461	0.317
			Shadow	127 (45)	0.615	0.837	**+0.222***	<0.001	0.034	0.004	0.201
Deposits (collapse)	Monthly macro	24	Composite (all three)	115 (54)	0.549	0.778	+0.230	<0.001	0.166	0.002	0.317
			Composite (Demand + Distress)	115 (54)	0.549	0.602	+0.053	0.154	0.021	0.276	0.194
			Demand	115 (54)	0.549	0.583	+0.034	0.414	0.111	0.563	0.278
			Distress	115 (54)	0.549	0.631	**+0.082***	0.023	0.016	0.074	0.165
			Shadow	115 (54)	0.549	0.698	+0.149	0.006	0.382	0.029	0.519
Deposits (collapse)	Credit-to-GDP gap	3	Composite (all three)	132 (30)	0.870	0.750	−0.120‡	0.016	0.131	0.045	0.361
			Composite (Demand + Distress)	132 (30)	0.870	0.764	−0.106‡	0.003	0.567	0.013	0.853
			Demand	132 (30)	0.870	0.771	−0.099‡	0.001	0.741	0.006	0.918
			Distress	132 (30)	0.870	0.805	−0.065	0.060	0.119	0.116	0.346
			Shadow	132 (30)	0.870	0.788	−0.082	0.143	0.027	0.226	0.191
Deposits (collapse)	Credit-to-GDP gap	6	Composite (all three)	132 (38)	0.878	0.671	−0.207‡	<0.001	0.100	<0.001	0.316
			Composite (Demand + Distress)	132 (38)	0.878	0.721	−0.156‡	<0.001	0.612	<0.001	0.877
			Demand	132 (38)	0.878	0.742	−0.136‡	<0.001	0.482	<0.001	0.766
			Distress	132 (38)	0.878	0.760	−0.118‡	0.006	0.312	0.021	0.600
			Shadow	132 (38)	0.878	0.694	−0.184‡	0.002	0.030	0.009	0.191

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
Deposits (collapse)	Credit-to-GDP gap	12	Composite (all three)	127 (45)	0.708	0.537	−0.171‡	<0.001	0.102	<0.001	0.316
			Composite (Demand + Distress)	127 (45)	0.708	0.618	−0.090‡	<0.001	0.515	0.001	0.789
			Demand	127 (45)	0.708	0.670	−0.038‡	0.010	0.726	0.033	0.910
			Distress	127 (45)	0.708	0.602	−0.105‡	<0.001	0.079	0.003	0.283
			Shadow	127 (45)	0.708	0.585	−0.123‡	0.005	0.019	0.021	0.180
Deposits (collapse)	Credit-to-GDP gap	24	Composite (all three)	115 (54)	0.696	0.692	−0.004	0.576	0.129	0.683	0.360
			Composite (Demand + Distress)	115 (54)	0.696	0.658	−0.038‡	0.025	0.298	0.061	0.595
			Demand	115 (54)	0.696	0.566	−0.130‡	<0.001	0.678	<0.001	0.895
			Distress	115 (54)	0.696	0.682	−0.015	0.080	0.110	0.142	0.335
			Shadow	115 (54)	0.696	0.659	−0.037	0.174	0.930	0.265	0.979
Impaired	Monthly macro	3	Composite (all three)	127 (27)	0.553	0.543	−0.010	0.783	0.117	0.884	0.288
			Composite (Demand + Distress)	127 (27)	0.553	0.550	−0.003	0.931	0.106	0.952	0.275
			Demand	127 (27)	0.553	0.549	−0.004	0.892	0.101	0.939	0.271
			Distress	127 (27)	0.553	0.541	−0.011	0.718	0.127	0.832	0.292
			Shadow	127 (27)	0.553	0.506	−0.047	0.480	0.110	0.640	0.278
Impaired	Monthly macro	6	Composite (all three)	124 (39)	0.546	0.559	+0.013	0.688	0.055	0.809	0.243
			Composite (Demand + Distress)	124 (39)	0.546	0.557	+0.011	0.725	0.056	0.832	0.243
			Demand	124 (39)	0.546	0.550	+0.004	0.905	0.065	0.939	0.247
			Distress	124 (39)	0.546	0.561	+0.015	0.565	0.046	0.726	0.222
			Shadow	124 (39)	0.546	0.503	−0.043	0.316	0.079	0.461	0.250
Impaired	Monthly macro	12	Composite (all three)	118 (57)	0.486	0.404	−0.083†‡	0.020	0.075	0.072	0.250
			Composite (Demand + Distress)	118 (57)	0.486	0.426	−0.061†	0.124	0.100	0.228	0.271

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Demand	118 (57)	0.486	0.420	−0.067†	0.095	0.122	0.192	0.292
			Distress	118 (57)	0.486	0.411	−0.075†‡	0.026	0.092	0.075	0.263
			Shadow	118 (57)	0.486	0.426	−0.060†	0.192	0.051	0.320	0.236
Impaired	Monthly macro	24	Composite (all three)	106 (84)	0.628	0.464	−0.163‡	0.002	0.068	0.014	0.248
			Composite (Demand + Distress)	106 (84)	0.628	0.547	−0.081	0.051	0.095	0.117	0.265
			Demand	106 (84)	0.628	0.544	−0.083‡	0.041	0.132	0.098	0.294
			Distress	106 (84)	0.628	0.570	−0.058	0.157	0.063	0.276	0.247
			Shadow	106 (84)	0.628	0.432	−0.195‡	0.003	0.179	0.023	0.326
Impaired	Credit-to-GDP gap	3	Composite (all three)	127 (27)	0.546	0.516	−0.030	0.275	0.769	0.377	0.944
			Composite (Demand + Distress)	127 (27)	0.546	0.550	+0.004	0.863	0.248	0.888	0.522
			Demand	127 (27)	0.546	0.573	+0.027	0.470	0.342	0.590	0.630
			Distress	127 (27)	0.546	0.515	−0.031‡	0.029	0.333	0.069	0.621
			Shadow	127 (27)	0.546	0.551	+0.006	0.939	0.249	0.945	0.522
Impaired	Credit-to-GDP gap	6	Composite (all three)	124 (39)	0.656	0.595	−0.060‡	0.048	0.597	0.098	0.877
			Composite (Demand + Distress)	124 (39)	0.656	0.622	−0.034	0.239	0.143	0.342	0.368
			Demand	124 (39)	0.656	0.604	−0.052	0.191	0.309	0.284	0.600
			Distress	124 (39)	0.656	0.630	−0.026‡	0.045	0.017	0.095	0.180
			Shadow	124 (39)	0.656	0.583	−0.073	0.183	0.454	0.276	0.746
Impaired	Credit-to-GDP gap	12	Composite (all three)	118 (57)	0.620	0.594	−0.026	0.284	0.237	0.386	0.522
			Composite (Demand + Distress)	118 (57)	0.620	0.601	−0.019	0.471	0.027	0.590	0.191
			Demand	118 (57)	0.620	0.607	−0.014	0.618	0.351	0.710	0.630
			Distress	118 (57)	0.620	0.585	−0.035‡	0.023	0.021	0.059	0.180

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Shadow	118 (57)	0.620	0.647	+0.027	0.507	0.173	0.612	0.403
Impaired	Credit-to-GDP gap	24	Composite (all three)	106 (84)	0.425	0.483	+0.058†	0.051	0.144	0.102	0.368
			Composite (Demand + Distress)	106 (84)	0.425	0.488	+0.063†	0.094	0.157	0.163	0.392
			Demand	106 (84)	0.425	0.464	+0.038†	0.301	0.677	0.405	0.895
			Distress	106 (84)	0.425	0.476	+0.050†	0.058	0.014	0.114	0.180
			Shadow	106 (84)	0.425	0.297	−0.129†‡	0.017	0.701	0.045	0.908
House price boom	Monthly macro	3	Composite (all three)	130 (4)	0.768	0.738	−0.030	0.332	0.198	0.479	0.348
			Composite (Demand + Distress)	130 (4)	0.768	0.760	−0.008	0.897	0.076	0.939	0.250
			Demand	130 (4)	0.768	0.696	−0.071	0.347	0.225	0.486	0.375
			Distress	130 (4)	0.768	0.875	**+0.107***	0.017	0.017	0.068	0.165
			Shadow	130 (4)	0.768	0.812	+0.044	0.544	0.929	0.705	0.977
House price boom	Monthly macro	6	Composite (all three)	127 (7)	0.748	0.732	−0.015	0.455	0.211	0.612	0.360
			Composite (Demand + Distress)	127 (7)	0.748	0.775	+0.027	0.339	0.057	0.480	0.244
			Demand	127 (7)	0.748	0.701	−0.046	0.187	0.177	0.316	0.326
			Distress	127 (7)	0.748	0.863	**+0.115***	0.025	0.014	0.074	0.162
			Shadow	127 (7)	0.748	0.742	−0.006	0.938	0.861	0.952	0.945
House price boom	Monthly macro	12	Composite (all three)	121 (7)	0.794	0.769	−0.025	0.233	0.962	0.367	0.990
			Composite (Demand + Distress)	121 (7)	0.794	0.793	−0.001	0.959	0.161	0.966	0.317
			Demand	121 (7)	0.794	0.736	−0.059‡	0.038	0.686	0.094	0.807
			Distress	121 (7)	0.794	0.823	+0.029	0.541	0.025	0.705	0.197
			Shadow	121 (7)	0.794	0.774	−0.020	0.815	0.631	0.905	0.755
House price boom	Monthly macro	24	Composite (all three)	109 (7)	0.657	0.521	−0.136	0.105	1.000	0.204	1.000
			Composite (Demand + Distress)	109 (7)	0.657	0.499	−0.158‡	0.024	0.897	0.074	0.966

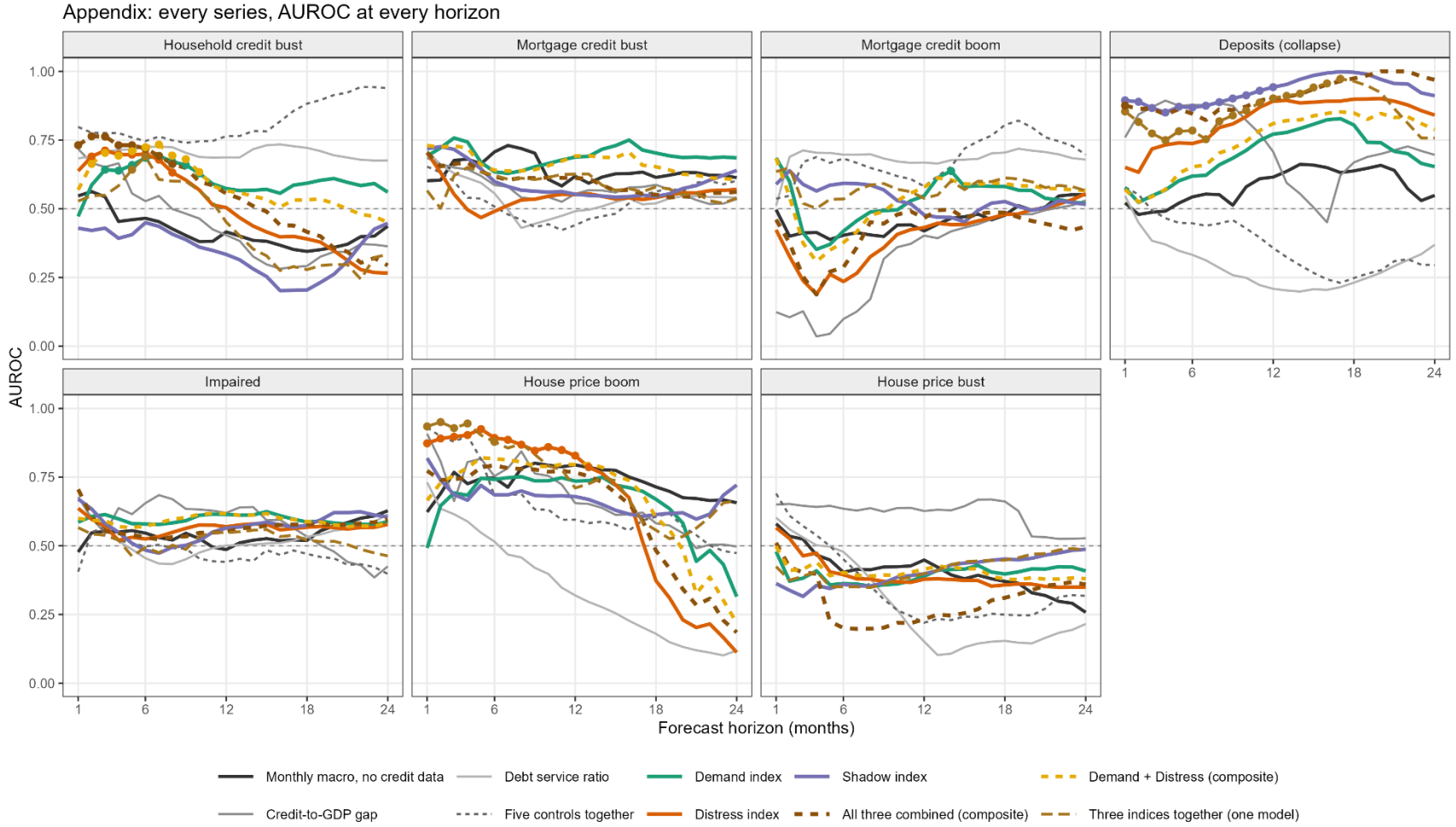
Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Demand	109 (7)	0.657	0.567	−0.090‡	0.022	0.943	0.074	0.977
			Distress	109 (7)	0.657	0.440	−0.217‡	0.035	0.845	0.090	0.942
			Shadow	109 (7)	0.657	0.850	+0.193	0.050	0.463	0.116	0.606
House price boom	Credit-to-GDP gap	3	Composite (all three)	130 (4)	0.663	0.720	+0.058	0.011	0.099	0.034	0.316
			Composite (Demand + Distress)	130 (4)	0.663	0.772	+0.109	0.012	0.051	0.037	0.228
			Demand	130 (4)	0.663	0.704	+0.042	0.274	0.098	0.377	0.316
			Distress	130 (4)	0.663	0.913	+0.250	0.113	0.029	0.183	0.191
			Shadow	130 (4)	0.663	0.597	−0.065	0.711	0.143	0.783	0.368
House price boom	Credit-to-GDP gap	6	Composite (all three)	127 (7)	0.754	0.765	+0.012	0.650	0.326	0.728	0.616
			Composite (Demand + Distress)	127 (7)	0.754	0.824	+0.070	0.103	0.019	0.176	0.180
			Demand	127 (7)	0.754	0.754	+0.000	1.000	0.162	1.000	0.398
			Distress	127 (7)	0.754	0.892	+0.138	0.134	0.002	0.215	0.086
			Shadow	127 (7)	0.754	0.648	−0.106	0.343	0.246	0.453	0.522
House price boom	Credit-to-GDP gap	12	Composite (all three)	121 (7)	0.655	0.818	+0.163	0.048	0.809	0.098	0.963
			Composite (Demand + Distress)	121 (7)	0.655	0.890	+0.234	0.011	0.353	0.034	0.630
			Demand	121 (7)	0.655	0.811	+0.155	0.202	0.458	0.298	0.746
			Distress	121 (7)	0.655	0.914	+0.258	0.003	0.257	0.012	0.522
			Shadow	121 (7)	0.655	0.635	−0.020	0.819	0.117	0.865	0.346
House price boom	Credit-to-GDP gap	24	Composite (all three)	109 (7)	0.497	0.373	−0.125†‡	0.017	0.356	0.045	0.630
			Composite (Demand + Distress)	109 (7)	0.497	0.419	−0.078†	0.075	0.142	0.138	0.368
			Demand	109 (7)	0.497	0.427	−0.070†	0.061	0.421	0.116	0.719
			Distress	109 (7)	0.497	0.409	−0.088†‡	0.040	0.072	0.088	0.283

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Shadow	109 (7)	0.497	0.664	+0.167†	0.036	0.077	0.082	0.283
House price bust	Monthly macro	3	Composite (all three)	130 (28)	0.524	0.538	+0.014	0.740	0.337	0.843	0.496
			Composite (Demand + Distress)	130 (28)	0.524	0.529	+0.005	0.822	0.387	0.905	0.521
			Demand	130 (28)	0.524	0.512	−0.012	0.584	0.351	0.733	0.507
			Distress	130 (28)	0.524	0.568	+0.044	0.158	0.210	0.276	0.360
			Shadow	130 (28)	0.524	0.480	−0.044	0.335	0.507	0.479	0.652
House price bust	Monthly macro	6	Composite (all three)	127 (34)	0.404	0.310	−0.094†	0.056	0.845	0.123	0.942
			Composite (Demand + Distress)	127 (34)	0.404	0.392	−0.012†	0.725	0.477	0.832	0.619
			Demand	127 (34)	0.404	0.369	−0.034†	0.363	0.566	0.503	0.701
			Distress	127 (34)	0.404	0.403	−0.001†	0.984	0.324	0.984	0.482
			Shadow	127 (34)	0.404	0.348	−0.056†	0.309	0.996	0.461	1.000
House price bust	Monthly macro	12	Composite (all three)	121 (46)	0.448	0.268	−0.180†‡	<0.001	0.588	0.006	0.716
			Composite (Demand + Distress)	121 (46)	0.448	0.388	−0.061†‡	0.013	0.585	0.053	0.716
			Demand	121 (46)	0.448	0.397	−0.052†	0.054	0.525	0.122	0.662
			Distress	121 (46)	0.448	0.360	−0.089†‡	<0.001	0.848	0.002	0.942
			Shadow	121 (46)	0.448	0.366	−0.083†	0.180	0.874	0.308	0.948
House price bust	Monthly macro	24	Composite (all three)	113 (68)	0.258	0.174	−0.084†‡	0.046	0.743	0.109	0.857
			Composite (Demand + Distress)	113 (68)	0.258	0.176	−0.082†‡	0.017	0.938	0.068	0.977
			Demand	113 (68)	0.258	0.197	−0.061†	0.110	0.779	0.211	0.887
			Distress	113 (68)	0.258	0.156	−0.102†‡	0.002	0.926	0.018	0.977
			Shadow	113 (68)	0.258	0.458	+0.200†	0.007	0.313	0.035	0.476
House price bust	Credit-to-GDP gap	3	Composite (all three)	130 (28)	0.646	0.566	−0.080‡	0.017	0.658	0.045	0.894
			Composite (Demand + Distress)	130 (28)	0.646	0.549	−0.097‡	0.008	0.393	0.027	0.679

Outcome	Baseline	h	Addition	N (events)	Baseline AUROC	AUROC	Δ AUROC	p DeLong	p Clark–West	q DeLong	q Clark–West
			Demand	130 (28)	0.646	0.538	−0.108‡	0.005	0.728	0.021	0.910
			Distress	130 (28)	0.646	0.639	−0.007	0.841	0.078	0.879	0.283
			Shadow	130 (28)	0.646	0.473	−0.173‡	<0.001	0.826	0.005	0.971
House price bust	Credit-to-GDP gap	6	Composite (all three)	127 (34)	0.635	0.567	−0.068‡	0.006	0.727	0.021	0.910
			Composite (Demand + Distress)	127 (34)	0.635	0.552	−0.083‡	0.009	0.633	0.029	0.877
			Demand	127 (34)	0.635	0.512	−0.123‡	0.001	0.882	0.006	0.979
			Distress	127 (34)	0.635	0.638	+0.003	0.921	0.085	0.934	0.299
			Shadow	127 (34)	0.635	0.451	−0.184‡	<0.001	0.812	0.005	0.963
House price bust	Credit-to-GDP gap	12	Composite (all three)	121 (46)	0.627	0.567	−0.060‡	<0.001	0.983	<0.001	0.990
			Composite (Demand + Distress)	121 (46)	0.627	0.592	−0.035	0.079	0.589	0.142	0.877
			Demand	121 (46)	0.627	0.537	−0.090‡	<0.001	0.874	0.005	0.979
			Distress	121 (46)	0.627	0.648	+0.021	0.229	0.071	0.331	0.283
			Shadow	121 (46)	0.627	0.442	−0.184‡	0.006	0.720	0.021	0.910
House price bust	Credit-to-GDP gap	24	Composite (all three)	113 (68)	0.528	0.414	−0.114‡	<0.001	0.878	<0.001	0.979
			Composite (Demand + Distress)	113 (68)	0.528	0.472	−0.056‡	0.003	0.518	0.014	0.789
			Demand	113 (68)	0.528	0.456	−0.072‡	0.002	0.860	0.010	0.979
			Distress	113 (68)	0.528	0.524	−0.004	0.796	0.048	0.857	0.226
			Shadow	113 (68)	0.528	0.408	−0.120	0.148	0.255	0.230	0.522

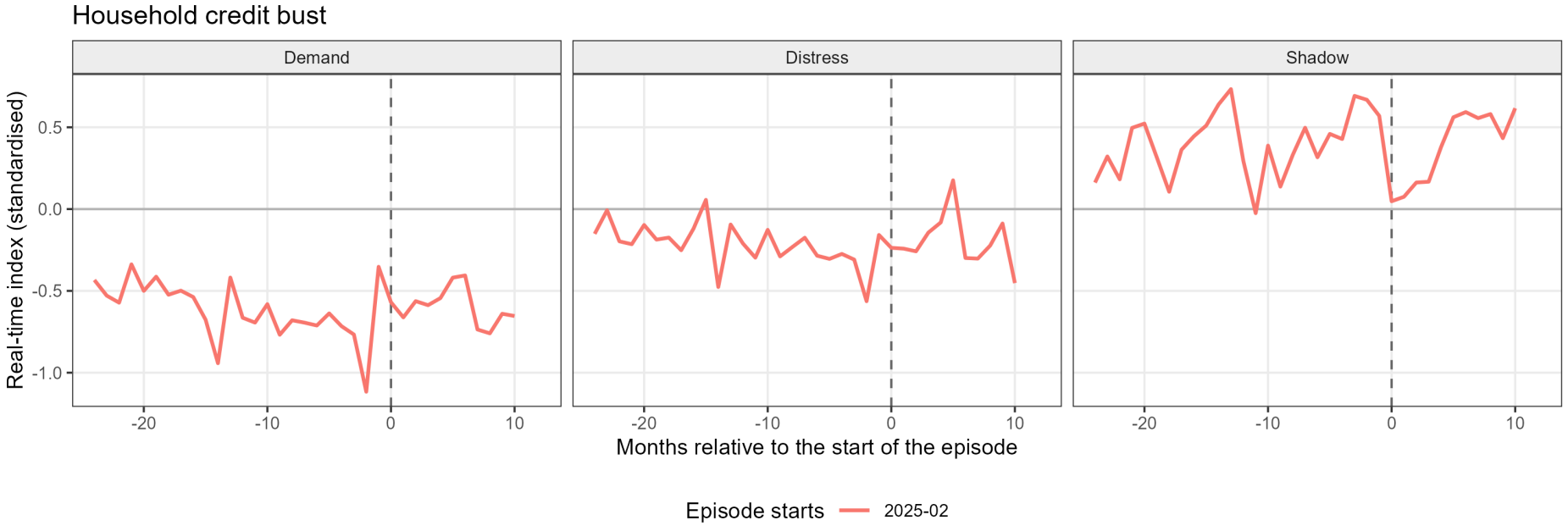
Notes: Each row adds one term to the baseline. Composite (all three) = mean of the Demand, Distress and Shadow indices; Composite (Demand + Distress) = mean of the first two. h = forecast horizon in months; N (events) = forecast origins on which both models are compared and, in brackets, how many of them are labelled as an episode starting within the horizon. p DeLong = paired DeLong test of the two AUROCs (two-sided); p Clark–West = Clark–West test on the Brier loss (Newey–West variance, bandwidth = horizon); q = Benjamini–Hochberg adjusted p, computed separately for each test and each baseline over all 140 tests (7 outcomes, 5 additions, 4 horizons). * = better on both tests (unadjusted $p < 0.05$); † = baseline AUROC below 0.5; ‡ = significantly worse on the DeLong test. After correction the DeLong test rejects in 86 of 280 comparisons and the Clark–West test in 1 (Mortgage credit boom, gap baseline, 24 months, Demand index).

Figure A1: All series by horizon



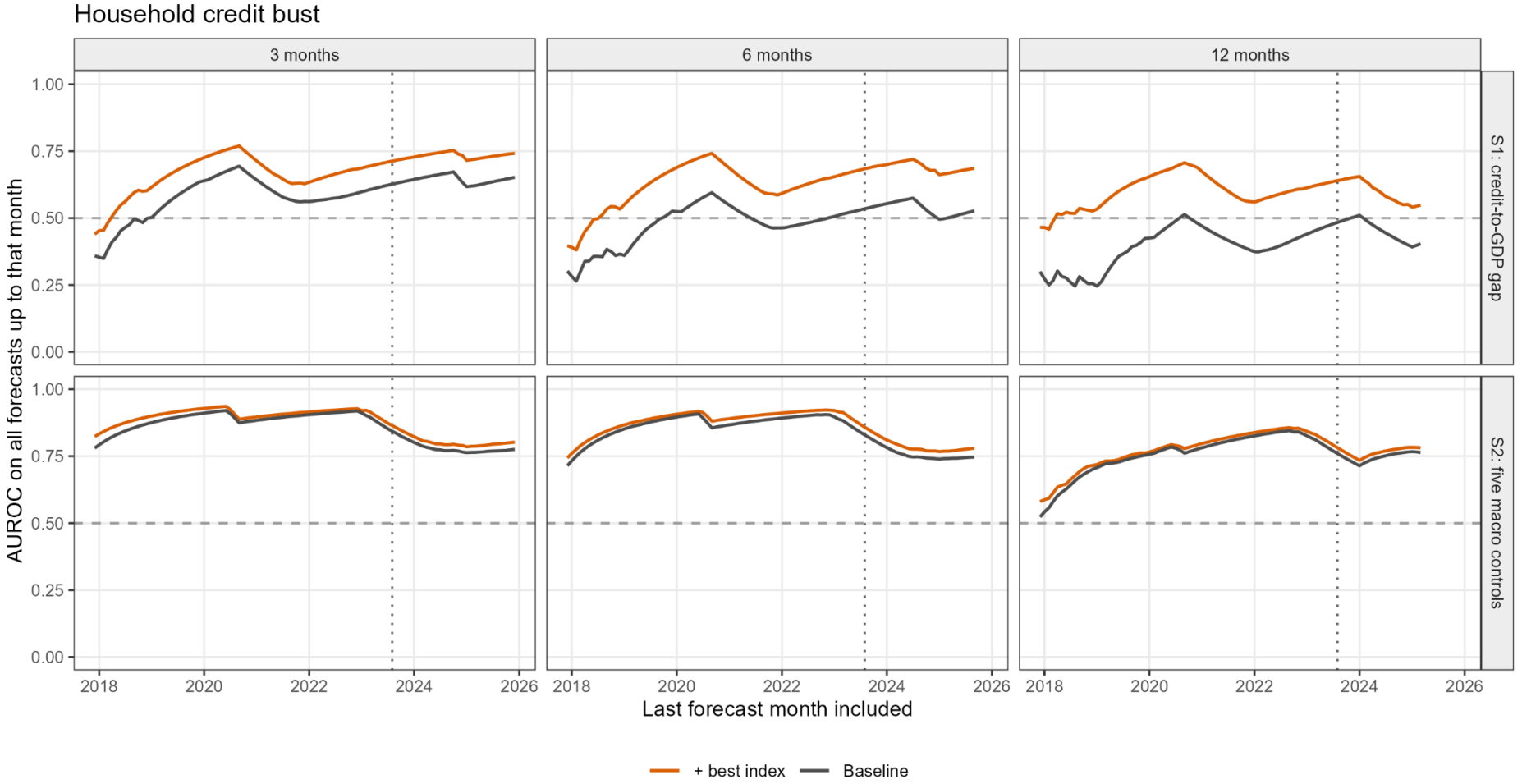
Note: AUROC of every series at every forecast horizon, by outcome. Real-time out-of-sample forecasts; each series on its own; event = an episode starts within the next h months. The dashed horizontal line is 0.5 (a coin toss). Coloured lines are the behavioural indices, solid for each index on its own and dashed for the Demand and Distress composite, the composite of all three indices and the three indices entered together in one model; dots mark the horizons at which the 95% DeLong interval excludes 0.5 and the Clark–West test against the constant forecast has $p < 0.05$. Black and grey lines are benchmarks: Monthly macro is the repo rate, CPI and leading indicator together (no credit or balance-sheet data); the credit-to-GDP gap, the debt service ratio and the five controls together use credit and household balance-sheet data. DeLong treats the overlapping monthly forecasts as independent and is generous; neighbouring horizons share most of their information. Event counts by outcome are in Table 5; the months labelled positive come in blocks, so the number of independent episodes is much smaller

Figure A2: Indices around episodes



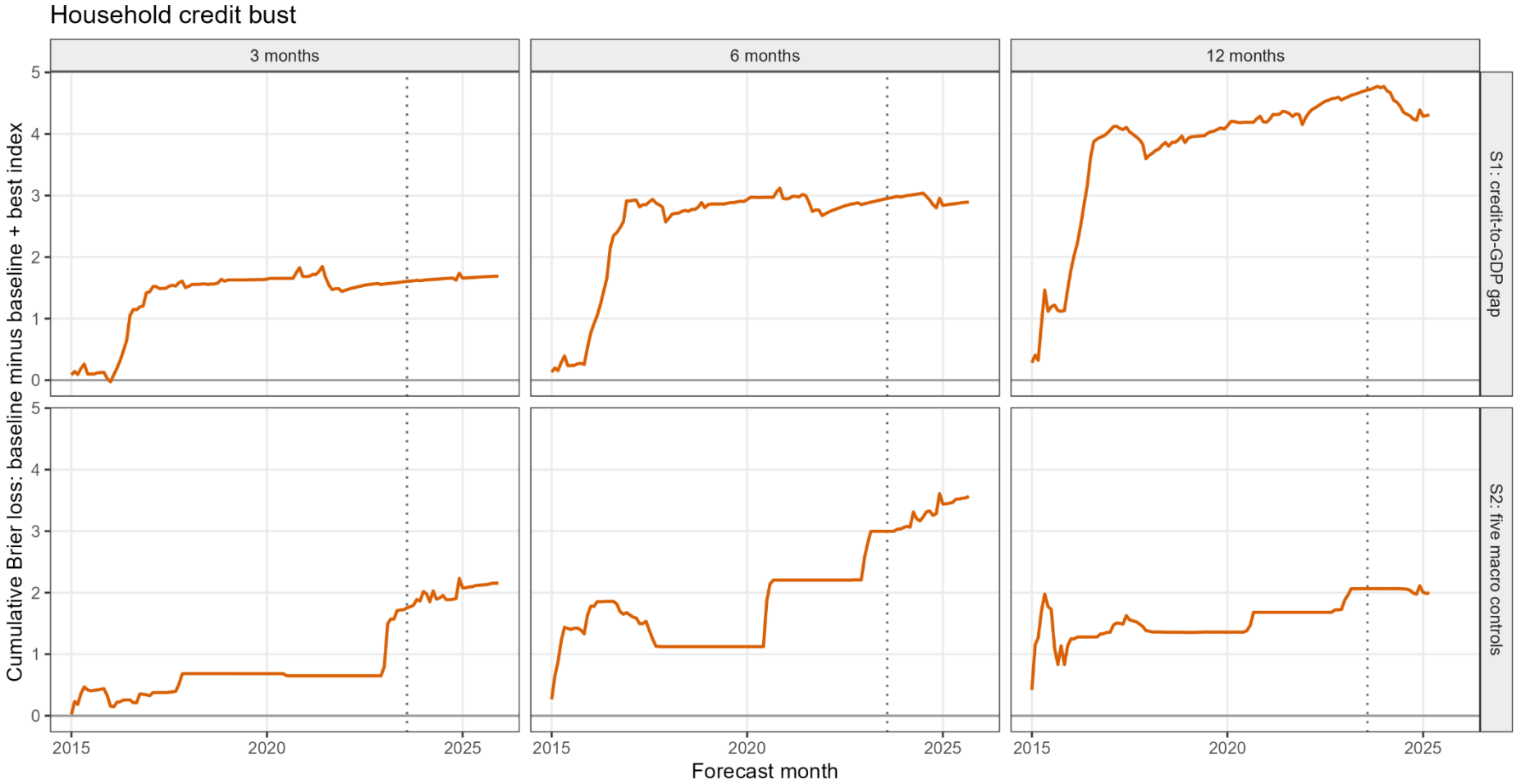
Month 0: the month in which the breach of the rolling real-time cutoff has lasted 2 month(s) (the sustained-episode rule), after at least 12 months without one; 1 episode(s) in the forecasting sample. One line per episode.

Figure A3: AUROC through time



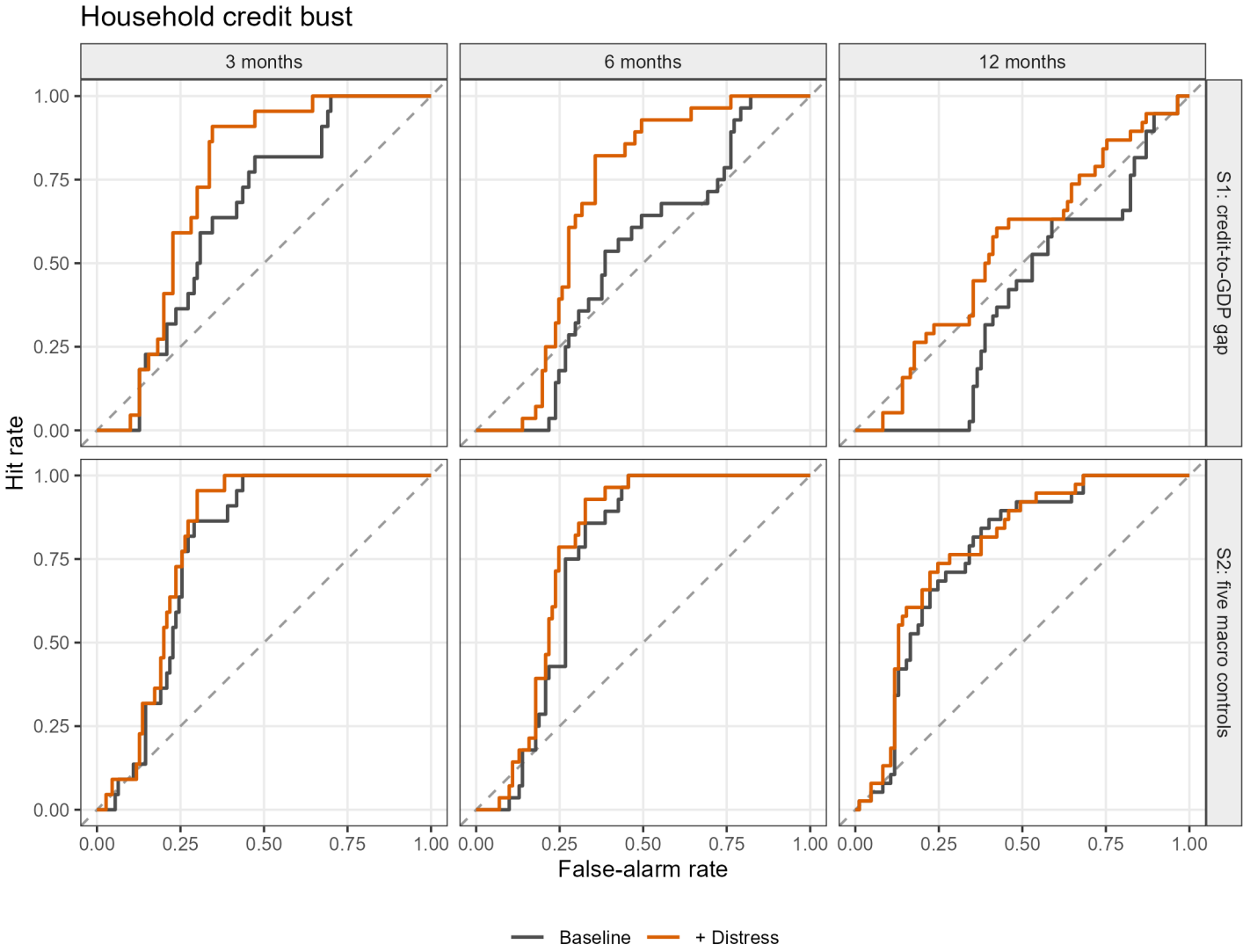
Expanding record of real-time forecasts (shown once it holds at least 5 events and 5 non-events). Dotted line: start of the final 36 months.

Figure A4: Cumulative loss



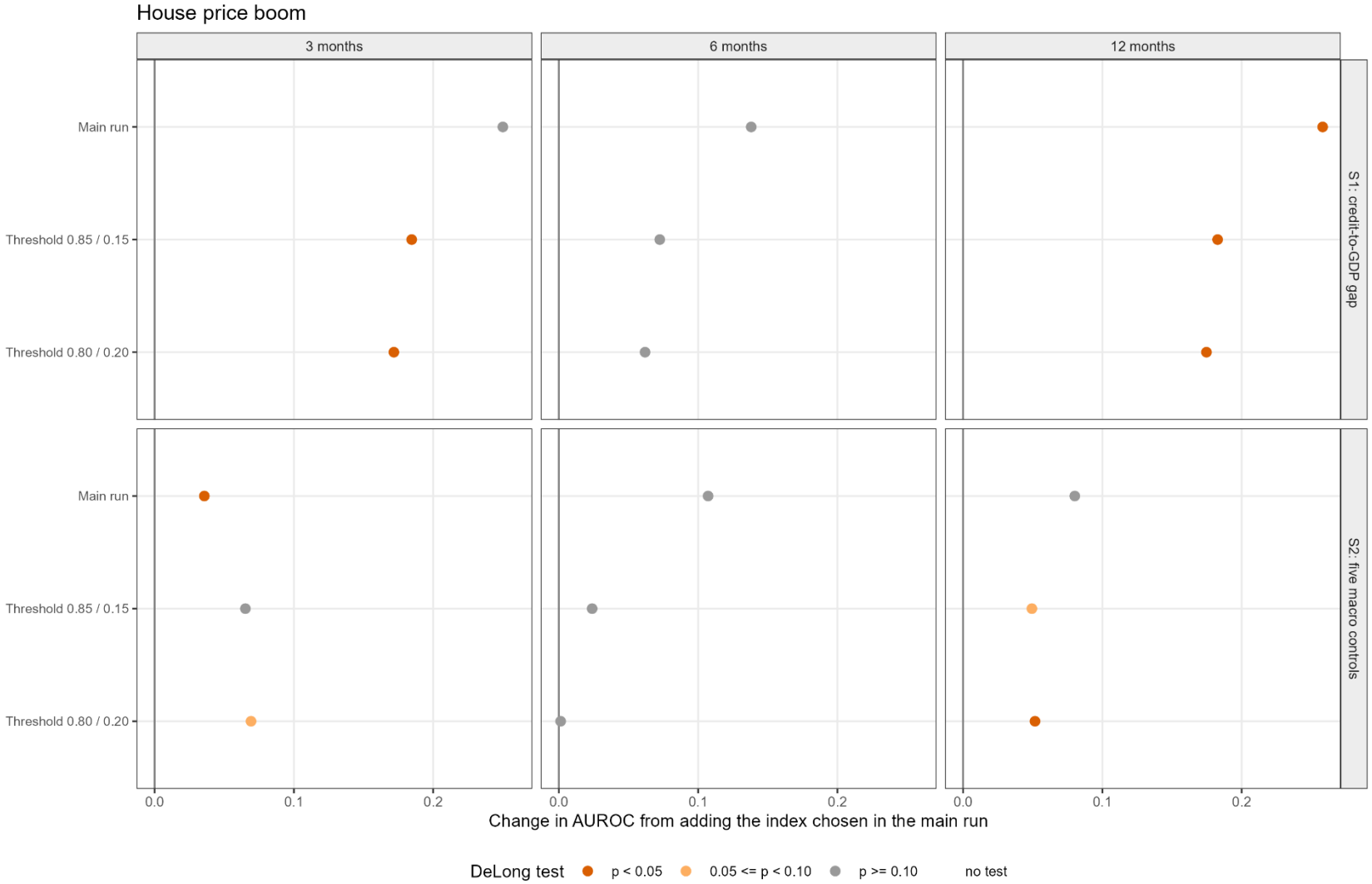
Rising = the behavioural index improves the forecast; a rise confined to one stretch means one episode drives the gain. Dotted line: start of the final 36 months.

Figure A5: ROC curves



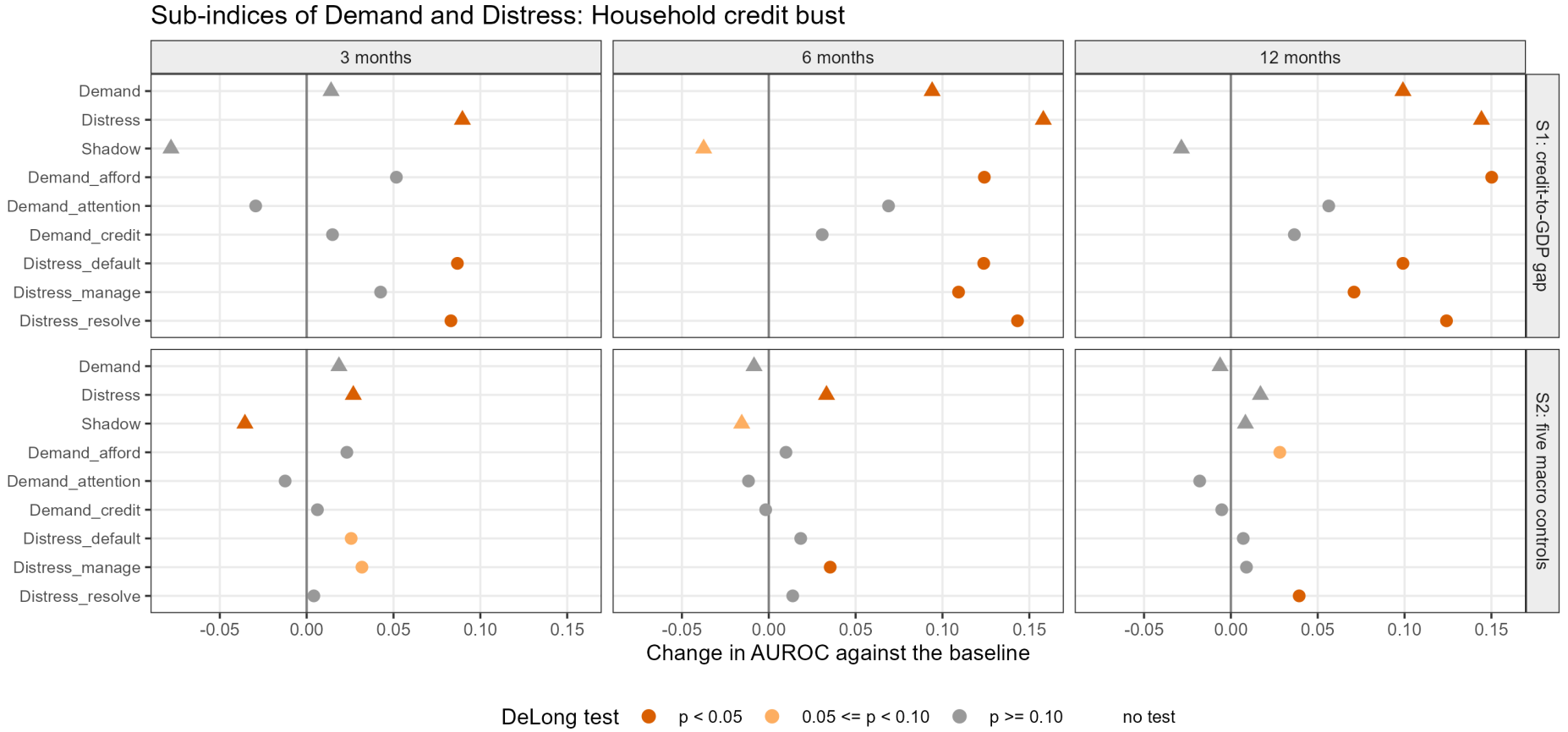
Pooled real-time out-of-sample forecasts, baseline against baseline plus the best behavioural index.

Figure A6: House price boom sensitivity



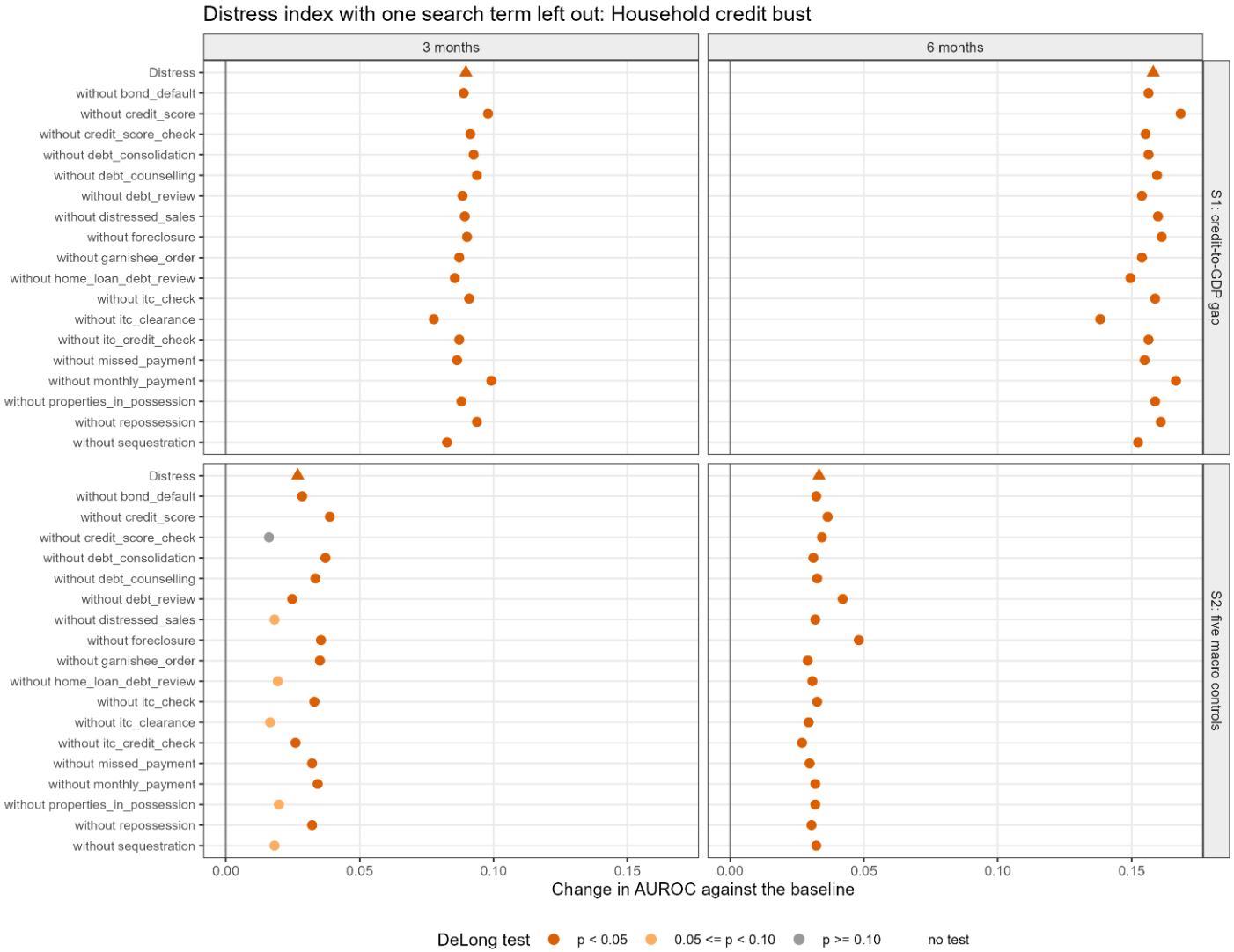
Each point: one scenario, same index as the main run (Distress/Shadow), re-estimated in real time. Own-lag: the baseline also contains the outcome's own lagged value. Placebo: the indices are shifted in time.

Figure A7: Sub indices



Triangle = the full index. Real-time out-of-sample forecasts.

Figure A8: Leave-one-out term



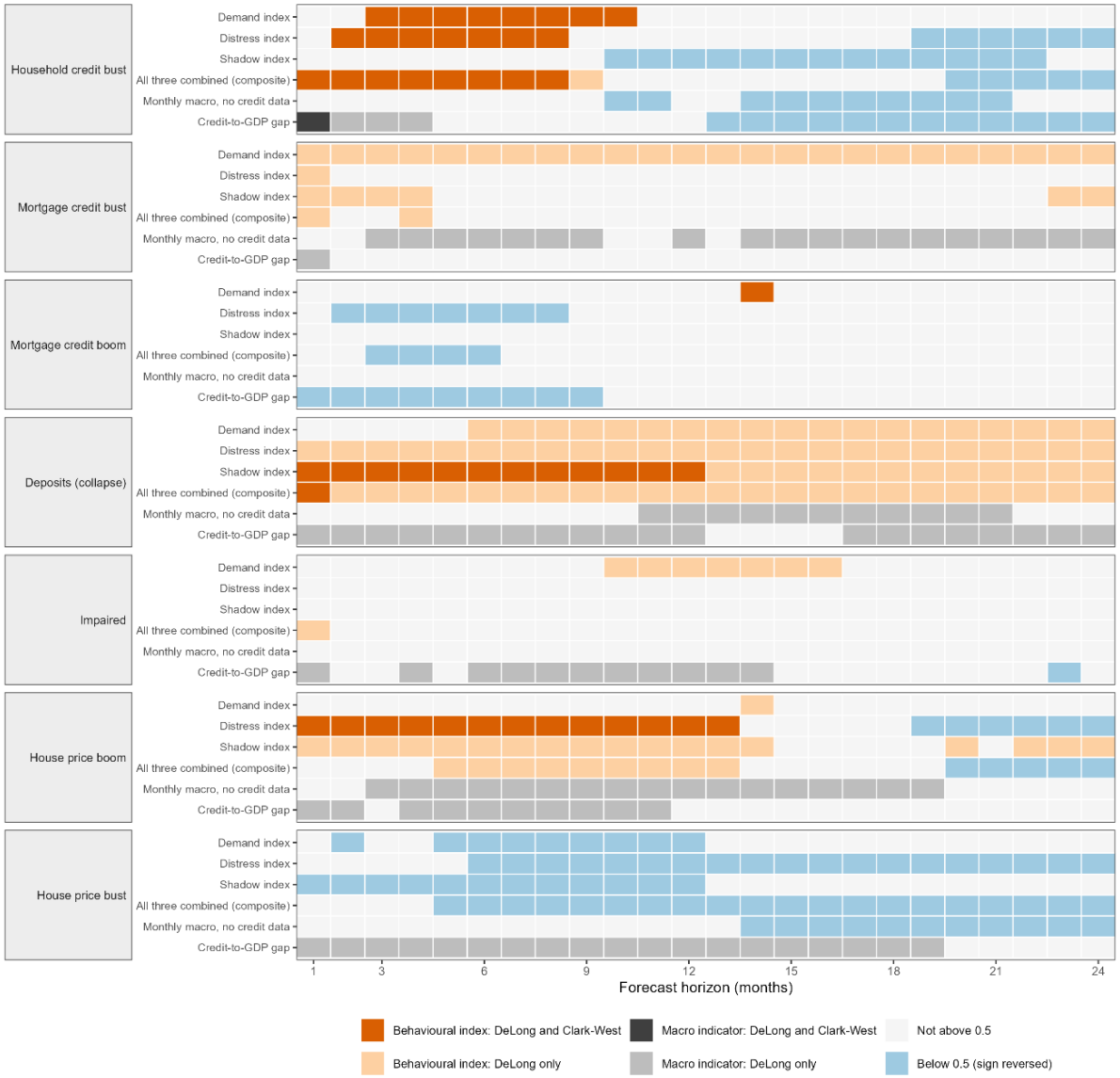
Triangle = the full index. Real-time out-of-sample forecasts.

Table A3. Correlations between the three behavioural indices

	Demand index	**Distress index**	**Shadow index**
Demand index	1	0.38	−0.46
Distress index	0.57	1	0.12
Shadow index	−0.35	0.04	1

Notes: Pearson correlations of the real-time indices. Below the diagonal: full sample (Jan 2010 to Dec 2025; N = 181 Demand–Distress, 169 Demand–Shadow, 169 Distress–Shadow). Above the diagonal: forecast period (Jan 2015 to Dec 2025; N = 132, 132, 132).

Figure A9: Lead time map, where each indicator is above 0.5



Note: Each tile is one indicator at one forecast horizon (1 to 24 months) for one outcome; real-time out-of-sample forecasts, each indicator on its own; event = an episode starts within the next h months. Dark orange (behavioural index) or dark grey (macro indicator): AUROC above 0.5 on both the 95% DeLong interval and the Clark–West test ($p < 0.05$). Light orange or light grey: above 0.5 on the DeLong interval only. Blue: the 95% DeLong interval lies below 0.5 (sign reversed). Blank: not above 0.5. 'Monthly macro' = repo rate, CPI and leading indicator together (no credit or balance-sheet data). DeLong treats the overlapping monthly forecasts as independent and is generous; neighbouring horizons share most of their information.