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DOOMBOT: A MACHINE LEARNING ALGORITHM FOR PREDICTING DOWNTURNS IN OECD COUNTRIES

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ABSTRACT / RESUME

Doombot: a machine learning algorithm for predicting downturns in OECD countries

This paper describes an algorithm, “DoomBot”, which selects parsimonious models to predict downturns over different quarterly horizons covering the ensuing two years for 20 OECD countries. The models are country- and horizon-specific and are automatically updated as the estimation sample period is extended, so facilitating out-of-sample evaluation of the algorithm. A limited combination of explanatory variables is chosen from a much larger pool of potential variables that include those that have been most useful in predicting downturns in previous OECD work. The most frequently selected variables are financial variables, especially those relating to credit and house prices, but also include equity prices and various measures of interest rates (such as the slope of the yield curve). Business cycle variables -- survey measure of capacity utilisation, industrial production, GDP and unemployment -- are also selected, but more frequently at very short horizons. The variables selected do not just relate to the domestic economy of the country being considered, but also international aggregates, consistent with findings from previous OECD work. The in-sample fit of the models is very good on standard performance metrics, although the out-of-sample performance is less impressive. The models do, however, provide a clear out-of-sample early warning of the Global Financial Crisis (GFC), especially when considered collectively, although they do generate ‘false alarms’ just ahead of the crisis. The models are less good at predicting the euro area crisis out-of-sample, but it is clear from the evolution of the choice of variables that the algorithm learns from this episode, for example through the more frequent selection of a variable measuring euro area sovereign bond spreads. The latest out-of-sample predictions made in mid-2023, suggest the probability of a downturn is at its greatest and most widespread since the GFC, with the largest contributions to such risks coming from house prices, interest rate developments (as measured by the slope of the yield curve and the rapidity of the change in short rates) and oil prices. On the other hand, warning signals from business cycle variables and equity prices, which are often good downturn predictors at short horizons, are conspicuously absent.

Keywords: Downturn, recession, forecast, GDP growth, risk.

JEL: E65, E17, E01, E66, E58.

Doombot : un algorithme d'apprentissage automatique pour prédire les ralentissements dans les pays de l'OCDE

Cet article décrit un algorithme, « DoomBot », qui sélectionne des modèles parcimonieux pour prédire les ralentissements sur différents horizons trimestriels couvrant les 2 années suivantes pour 20 pays de l'OCDE. Les modèles sont spécifiques au pays et à l'horizon et sont automatiquement mis à jour à mesure que la période d'échantillonnage d'estimation est prolongée, facilitant ainsi l'évaluation hors échantillon de l'algorithme. Une combinaison limitée de variables explicatives est choisie parmi un ensemble beaucoup plus large de variables potentielles qui incluent celles qui ont été les plus utiles pour prédire les ralentissements dans les travaux antérieurs de l'OCDE. Les variables les plus fréquemment sélectionnées sont les variables financières, en particulier celles relatives au crédit et aux prix de l'immobilier, mais incluent également les prix des actions et diverses mesures des taux d'intérêt (comme la pente de la courbe des taux). Les variables du cycle économique - mesure d'enquête de l'utilisation des capacités, de la production industrielle, du PIB et du chômage - sont également sélectionnées, mais plus fréquemment à des horizons très courts. Les variables sélectionnées ne se rapportent pas seulement à l'économie nationale du pays considéré, mais également à des agrégats internationaux, conformément aux conclusions de travaux antérieurs de l'OCDE. L'ajustement dans l'échantillon des modèles est très bon sur les mesures de performance standard, bien que la performance hors échantillon soit moins impressionnante. Les modèles fournissent cependant une alerte précoce claire hors échantillon de la crise financière mondiale (GFC), en particulier lorsqu'ils sont considérés collectivement, bien qu'ils génèrent de «fausses alarmes» juste avant la crise. Les modèles sont moins bons pour prédire la crise de la zone euro hors échantillon, mais il ressort clairement de l'évolution du choix des variables que l'algorithme apprend de cet épisode, par exemple à travers la sélection plus fréquente d'une variable mesurant les spreads des obligations souveraines de la zone euro. Les dernières prévisions hors échantillon faites à la mi-2023 suggèrent que la probabilité d'un ralentissement est la plus élevée et la plus répandue depuis la GFC, les contributions les plus importantes à ces risques provenant des prix de l'immobilier, de l'évolution des taux d'intérêt (mesurée par la pente de la courbe des taux et la rapidité de la variation des taux courts) et des prix du pétrole. D'autre part, les signaux d'alarme des variables du cycle économique et des cours des actions, qui sont souvent de bons prédicteurs de ralentissement à court terme, sont manifestement absents.

Mots clés : Ralentissement, récession, prévision, croissance du PIB, risque.

JEL : E65, E17, E01, E66, E58:

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Doombot: a machine learning algorithm for predicting downturns in OECD countries

By: Thomas Chalaux and David Turner[1]

1. Introduction and summary

1. Macroeconomic forecasters are notoriously bad at predicting downturns and this failure consistently accounts for their largest forecast errors (for example: Loungani, 2001; Abreu, 2011; Fildes and Steckler, 2002; Pain and Lewis, 2014; An et al., 2018). This failure is sometimes mitigated by accompanying commentary that provides a descriptive account of risks surrounding the forecasts (Cleach et al, forthcoming). The current paper describes an alternative and possibly complementary approach by providing a quantitative assessment of the risks of a downturn over a two-year forecast horizon. Drawing on previous OECD work (Hermansen and Röhn, 2016; Caldera Sánchez, et al., 2017; Turner et al., 2019), the probability of a future downturn is derived from country-specific probit models, which use financial and business cycle variables with both a domestic and international scope, to predict downturns in 20 OECD countries at a range of quarterly horizons up to two years. An important elaboration of the methodology employed in this paper compared to previous work, is that an algorithm, "DoomBot", is employed to select the 'best' model for each horizon and country as the estimation period is extended as more data becomes available.[2]

2. This paper can be seen as part of a recent trend in macroeconomic forecasting research, which involves a fusion of traditional and modern machine learning approaches. Traditional methodologies, exemplified by Reinhart and Rogoff (2008), Estrella and Mishkin (1996), Stock and Watson (2010) and Greenwood et al. (2022), emphasise a range of financial variables in predicting financial crises or recessions. Conversely, contemporary machine learning approaches, as seen in Davis and Karim (2008), Tölö (2020), Fouliard et al. (2021), Holopainen and Sarlin (2017) or Hellwig (2021), leverage advanced computational techniques with extensive datasets that take a more agnostic approach as to what

[1] The authors are members of the Macroeconomic Analysis Division of the OECD Economics Department. They would like to thank Nigel Pain and Lucia Quaglietti for detailed and thoughtful comments on a previous draft, Country Desk economists in the OECD Economics Department whose probing questions on early presentations of the work led to further evolutions, as well as Veronica Humi for help with the editorial process.

[2] The algorithm is run to update the models to correspond with the publications dates and forecast horizons of the *OECD Economic Outlook*: for the Spring edition (typically published in May or early June) where the first quarter of the publication year is known, seven quarters of forecasts are necessary to obtain the current and year-ahead forecasts; for the Autumn edition (typically published in November or early December), where the third quarter of the publication year is known, 9 quarters of forecasts are necessary to obtain the current, year-ahead and two-years ahead forecasts.

explanatory variables matter. Kiley (2018) provides a comprehensive literature review with findings consistent with this paper: financial variables, leading indicators of activity as well as more immediate measures of the business cycle can all contribute to forecasting recessions, with their usefulness varying across different horizons, while a singular focus on subsets or individual indicators, such as the yield curve, can give misleading results.

3. This paper applies a machine learning approach to the traditional modelling of recession probabilities, aiming to enhance robustness, accuracy and interpretability by leveraging the strength of both approaches. The methodology uses many features that are common to machine learning: an algorithm is used to pick statistical models following a data-intensive selection process where variable are chosen from a large pool of potential explanatory variables (which include both financial and business cycle activity indicators as well as both domestic and international indicators); the algorithm learns from experience so that the models evolve as the sample period is extended; the selection and updating of many models (for 20 countries, each over 9 different quarterly horizons) is automated using the same algorithm demonstrating that the approach is scalable; and many of the model evaluation metrics that are commonly used in machine learning are employed to evaluate the models. At the same time, sufficient judgemental constraints are imposed to ensure that the prediction equations chosen are parsimonious, consistent across horizons and so have a plausible interpretation, so addressing one of the common criticisms of machine learning methods.

4. Another important feature of the current work, compared to much of the traditional recession modelling literature, is that the same approach is applied to a large number of countries at different horizons, so providing a further test of its robustness. One advantage of using an algorithm is that it makes it easier to update as new data becomes available or to extend the approach to new countries or to consider the inclusion of new explanatory variables. A second advantage is that it provides a means of evaluating the out-of-sample historical performance of the algorithm, rather than relying only on within-sample evaluation, especially given that in-sample performance of probabilistic discrete choice models is often found to exaggerate their out-of-sample performance. Thus, in the current set-up, it is easy to run the algorithm to the eve of a major downturn, such as just prior to the Global Financial Crisis, and then evaluate the out-of-sample performance of the models in predicting the downturn.

5. The main findings of the paper can be summarised as follows:

- The variables selected depend on the horizon at which the downturn risk is being assessed. For the immediate quarter, business sector variables – survey measures of capacity utilisation, industrial production, (lagged) GDP and unemployment – account for about 30% of the variables selected, but much less at longer horizons. Over all horizons, credit and house prices are among the most frequently selected variables: domestic credit and house price variables account for 20-30% of variables selected at all horizons; and international measures of credit and house prices account for between 20-30% at all horizons. Other financial variables that are frequently selected include equity prices, accounting for 15-20% of variables selected at horizons between 1 and 4 quarters, as well as interest rates, measured by the slope of the yield curve or the rapidity of changes in short-term rates, which account for up to 10% of the variables selected. Beyond a horizon of the first two quarters, oil prices account for about 10% of the variables selected.
- The in-sample fit of the Doombot algorithm is very good, across virtually all countries and horizons, according to standard performance metrics. The out-of-sample performance is weaker and less consistent across countries, although in terms of predicting downturns it beats both a naïve forecast rule and the published *Economic Outlook* forecasts. A more detailed examination of the out-of-sample performance suggests that while the algorithm does a good job at predicting the Global Financial Crisis (GFC), its performance score is lowered because it also predicts elevated risks in the years prior to the GFC. However, arguably these early warnings should instead count positively as they could have provided policymakers with more time to take remedial action. For the euro

area crisis, the algorithm is less impressive, especially in picking up the breadth of the crisis across countries. This may be because the systemic nature of the crisis stemming from new monetary arrangements under the single currency are not sufficiently reflected in the sample period over which the models are estimated. However, after the crisis the algorithm selects much more frequently a measure of euro area sovereign bond spreads, which may enable it to detect a downturn having similar systemic origins in future.

- An inevitable weakness of the approach described here is that it will not capture downturns that are the consequence of unusual, one-off or idiosyncratic events for which there is little or no recent historical experience. This is most obviously the case for the global downturn caused by the COVID pandemic, which receives special treatment in the estimation procedure underlying the algorithm (as described in section 2.4). It also applies to other events such as the recent war in Ukraine. Still, it is striking that the overwhelming majority of downturns in OECD countries *are* captured by an approach using a common set of potential explanatory variables. A corollary is that, while it may not capture all risks, the algorithm serves as a starting point upon which to layer on consideration of more idiosyncratic shocks in any complete risk assessment.
- The latest Doombot predictions, made at the time this draft was being finalised in mid-2023, suggest that the risks of a downturn over the *Economic Outlook* horizon (to end 2024) are projected to be at their most elevated and widespread among OECD countries since the Global Financial Crisis. These probabilities are mostly generated by house prices, interest rate developments and oil prices, although contributions from business cycle variables (like survey measures of capacity utilisation or industrial production) and equity prices, both of which feature heavily at short horizons, are conspicuously absent.

6. The remainder of this paper is organised as follows. Section 2 defines the broad framework and scope of the paper, in terms of the country and time-period coverage, the definition of a downturn used throughout the paper, as well as the choice of potential explanatory variables that explain downturn episodes. Section 3 describes the algorithm that is used to select the probit downturn models, including a modification to the algorithm to use an alternative and simpler prediction rule, which is only employed once it is clear that the economy is already in a downturn. Section 4 evaluates the performance of the algorithm, with a particular focus on its performance ahead of the GFC. Section 5 describes the latest downturn predictions made in mid-2023 for the remainder of 2023 and 2024. A set of Annexes A to C provide charts and tables with more details of individual country models and their performance. A forthcoming companion paper will use the downturn probabilities described in this paper to construct fan charts around OECD forecasts (Turner and Chalaux, forthcoming).[3]

2. The broad framework

7. This section describes the scope of the modelling exercise in terms of the country and time period coverage, the definition of downturns and the pool of potential explanatory variables considered.

[3] Additional work, not reported in detail in this paper, suggests that the size of the downturn probabilities is related to the severity of the downturn to which they relate. Thus, in a pooled regression explaining quarterly GDP per capita, the coefficient on the full-sample downturn probabilities for that quarter is always strongly statistically significant (and negative) and this result is robust to the inclusion of country and/or horizon fixed effects and also whether the sample is based on all quarters or just downturn quarters. This relationship between the severity of downturns and the size of downturn probabilities will be exploited in future work to generate fan charts around *Economic Outlook* forecasts.

2.1. Country and time period coverage

8. The country coverage is dictated by the availability of data, particularly on credit and house prices, which previous OECD work suggest are good predictors of future downturns. The sample period for estimation begins in 1980, which gives sufficient data to test the model's out-of-sample predictions ahead of the Global Financial Crisis (GFC), whereas extending it further back into the 1970s is arguably problematic given major changes in financial markets since then. On this basis, 20 OECD countries are considered here:

- G7 economies: United States, Japan, Germany, France, the United Kingdom, Italy and Canada.
- Other EU countries: Austria, Belgium, Finland, Greece, Netherlands, Portugal and Spain.
- Other European countries: Denmark, Norway, Sweden and Switzerland.
- Other OECD countries: Australia and New Zealand.

The country sample could in future be extended to other OECD countries, although this would likely mean compromising on the inclusion of some data series as well as shortening the estimation sample, which in turn would make it difficult to test out-of-sample performance.

2.2. Definition of a downturn

9. The definition of a downturn differs across countries to ensure that for each country there are sufficient quarters (roughly 15%) of the total sample that are designated as downturns. To be designated as a downturn requires at least two consecutive quarters of negative growth in GDP per capita and for the cumulative output loss to exceed a country-specific threshold, which also varies over time.[4] More precisely, for most countries the threshold is defined as the moving average of the quarterly growth rate of GDP per capita less a moving average of one standard deviation of the quarterly growth of GDP per capita, where the moving average always begins in 1970. This calculation typically gives a threshold of between -0.5% and -1%, although the threshold varies over time as the end of the sample is incrementally extended from 1980. When the cumulated growth over consecutive negative quarters is below this threshold, the corresponding quarters are defined as downturns.

10. The downturns associated with the COVID-19 pandemic are problematic for the models estimated here, because their origin is not in the build-up of financial tensions associated with most other downturns. Hence, they are treated differently. Thus, while the fall in GDP related to the pandemic exceeds the threshold in all countries, given that its immediate cause is not related to conventional financial developments, it is designated as a non-downturn period for the purpose of the current modelling exercise.

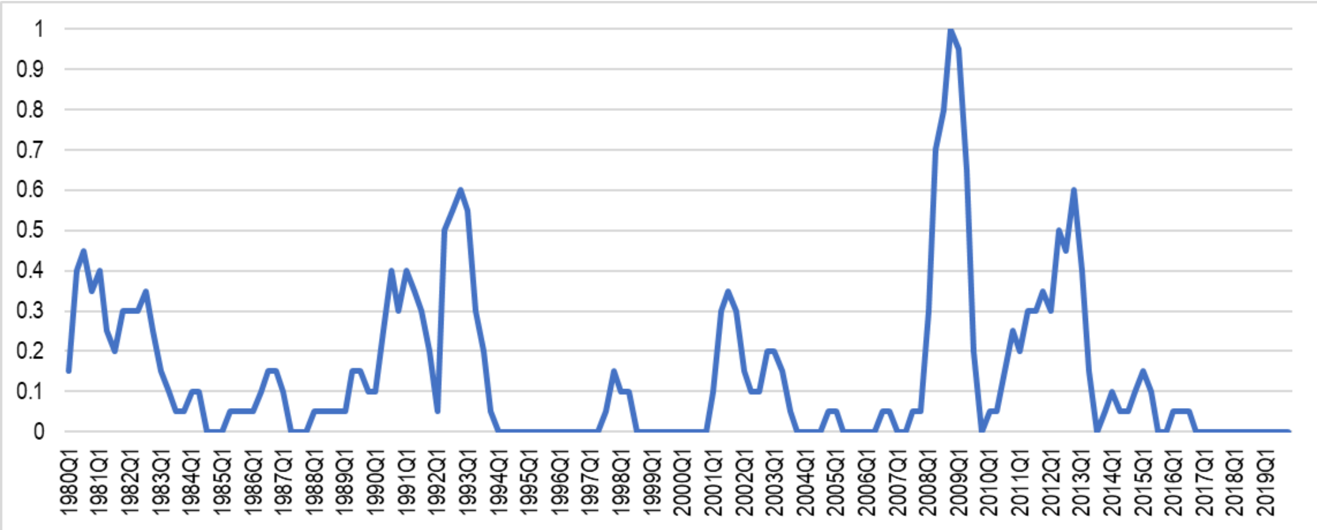
11. The identified downturns are highly synchronised across countries, with at least 40% of the OECD countries considered here simultaneously experiencing a downturn during the early 1980's, 1990's, the Global Financial Crisis and euro area crisis (Figure 1). A full list of all downturns for each of the 20 countries considered by the study is given in Table 1. [5]

[4] GDP per capita is used in preference to GDP because a given fall in GDP is more serious when the underlying population is growing strongly than if the population was stable or falling and, given that population growth varies both over time and between countries, normalising on population allows greater comparability across countries.

[5] Taking the United States as an illustrative example, when this definition is applied over the period 1980-2019, the quarters selected as downturns overlap closely with the quarters that are classified as recessions by the NBER. The main exception is that the NBER designate 2001Q2-Q4 as a recession, whereas on the definition used here this period does not qualify as a downturn because GDP per capita growth in 2001 Q3 was positive so there are not two quarters of consecutive negative growth.

Figure 1. Downturns are synchronised across countries

Share of 20 OECD countries designated to be in a downturn, 1980-2019



Note: The definition of a downturn is specific to this paper and is described in the text. Full details of the downturn periods for each of the 20 countries can be found in Annex A.

Table 1. Downturn episodes since 1980

	1980's	1990's	2000's	2010's	2020's	No. of downturns	Average length
AUS	81Q4-82Q1 ; 82Q3-83Q2	90Q2-90Q3 ; 91Q1-91Q2	08Q2-08Q4			5	3
AUT	80Q2-81Q1 ; 84Q1-84Q2	92Q3-93Q1	01Q1-01Q3 ; 08Q3-09Q2	12Q2-13Q2 ; 14Q3-15Q2		7	4
BEL	80Q3-81Q2	92Q2-93Q1	01Q1-01Q4 ; 08Q2-09Q2	12Q4-13Q1		5	4
CAN	80Q2-80Q3 ; 81Q3-82Q4 ; 86Q3-86Q4 ; 89Q2-89Q4	90Q2-91Q1 ; 91Q3-92Q2	08Q4-09Q2	15Q1-15Q2		8	3
CHE	81Q4-82Q4	90Q3-91Q4 ; 92Q2-93Q1	01Q3-02Q1 ; 02Q3-03Q2 ; 08Q4-09Q1	11Q3-11Q4		7	4
DEU	80Q2-80Q4 ; 82Q2-82Q3	91Q2-91Q3 ; 92Q2-93Q2	01Q2-02Q1 ; 02Q4-03Q1 ; 08Q2-09Q1	12Q4-13Q1	23Q1-?	8	3
DNK	80Q2-81Q1	92Q2-93Q1 ; 97Q3-97Q4	01Q4-02Q2 ; 06Q3-06Q4 ; 08Q1-09Q2			6	4
ESP	81Q1-81Q2	92Q4-93Q2	08Q1-09Q2	10Q3-13Q2		4	6
FIN	80Q4-81Q1	90Q2-91Q4 ; 92Q2-92Q4	08Q1-08Q2 ; 08Q4-09Q2	11Q4-13Q1 ; 13Q4-14Q1 ; 14Q4-15Q1	22Q3-22Q4	8	3
FRA		92Q3-93Q3	02Q4-03Q2 ; 08Q2-09Q3	12Q1-12Q2 ; 12Q4-13Q1 ; 14Q1-14Q2		6	3
GBR	80Q1-81Q1	90Q3-91Q3	08Q2-09Q3			3	5
GRC	80Q2-83Q1 ; 86Q2-87Q1 ; 89Q2-90Q1	92Q2-93Q1	04Q4-05Q1 ; 07Q3-07Q4 ; 08Q2-09Q1	10Q1-11Q4 ; 12Q2-13Q1		9	5
ITA	82Q1-82Q4	92Q2-93Q3	01Q2-01Q4 ; 03Q1-03Q3 ; 08Q2-09Q2	11Q2-13Q2		6	5
JPN		93Q2-93Q3 ; 97Q4-98Q2	01Q2-01Q4 ; 08Q2-09Q1	10Q4-11Q2 ; 12Q2-12Q4		6	3
NLD	80Q1-80Q3 ; 81Q1-81Q4		08Q3-09Q2	11Q2-12Q4	23Q1-?	4	5
NOR	81Q2-81Q3 ; 82Q2-82Q3 ; 86Q3-87Q1 ; 88Q1-89Q3	90Q1-90Q3	01Q2-01Q3 ; 08Q4-09Q3		23Q1-?	7	3
NZL	85Q2-86Q2	91Q1-91Q2 ; 97Q4-98Q2	08Q1-09Q1	10Q3-10Q4	23Q1-?	5	3
PRT	83Q1-84Q2	92Q2-93Q4	02Q2-02Q4 ; 08Q1-09Q1	10Q4-12Q4		5	6
SWE		90Q2-91Q4 ; 92Q2-93Q1	08Q1-09Q3	12Q2-12Q4 ; 16Q1-16Q3		5	5
USA	80Q1-80Q3 ; 81Q4-82Q1	90Q3-91Q1	08Q3-09Q2		22Q1-22Q2	5	3

Note: The definition of a downturn is country-specific, see text.

2.3. The potential set of variables explaining a downturn

12. The global set of possible variables to potentially explain downturns is based on those which have been found to have explanatory power in predicting downturns in OECD countries in previous OECD work (Table 2).

Table 2. Explanatory variables used to explain downturns.

Type of variable	Explanatory variable	Publication lag wrt GDP (quarters)	Short-term sign	Long-term sign
Business cycle	Capacity utilisation	1	-	+
	Industrial production	0	-	+
	Unemployment rate	0	+	-
	Real GDP per capita growth	0	-	+
Financial	Real share prices	1	-	+
	Yield curve slope	1	-	-
	Euro area interest spread	1	+	+
	Short-term interest rate	1	+	-
	Total credit share of GDP	-2	-	+
	Bank credit share of GDP	-2	-	+
	Real house prices	-1	-	+
	House price-to-rent ratio	-1	-	+
	House price-to-income ratio	-1	-	+
International	Oil prices	1	+	+
	Real share prices	1	-	+
	Total credit share of GDP	-2	-	+
	Bank credit share of GDP	-2	-	+
	Real house prices	-1	-	+

Note: The “signs” in the final two columns signify an imposed sign constraint on the corresponding variable in the probit equations explaining a downturn. “Short-term sign” applies to quarter-on-quarter and year-on-year changes or growth rates, whereas the “long-term sign” applies to the annual average growth rates or changes over three or five years. Additionally, “short-term sign” applies to functional forms intended to capture a point of inflexion, namely a short-term growth rate (such as year-on-year growth rate) *less* a long-term growth rate (such as the average growth rate over five years). The euro area aggregates can only enter the list of variables used for individual euro area countries. US variables can be included in the equations for Canada.

These variables include macroeconomic indicators related to the business cycle and variables capturing developments in financial markets:[6]

- The business cycle variables included are survey measures of capacity utilisation, the unemployment rate, GDP per capita and industrial production.
- The financial market variables included are those which previous OECD work (Hermansen and Röhn, 2016) found to be most reliable in predicting future downturns at horizons of up to two years across OECD countries, including credit growth, house prices and equity prices.
- Different functions of interest rates are also included: the slope of the yield curve, which has an established track record in predicting recessions in some countries most notably the United States (Estrella and Turbin, 2006); and changes in short-term interest rates, intended to capture the effect of a relatively rapid (and so perhaps unexpected) tightening of monetary policy.
- Previous OECD work also found that international or global indicators often outperformed domestic indicators and so various international aggregates of financial variables as well as oil prices are included among the possible set of variables to explain country-specific downturn probabilities. These aggregates include those for the OECD and the euro area. For euro area countries only,

[6] A possible criticism of the choice of potential explanatory variables, particularly for the purpose of conducting out-of-sample evaluations relating to the GFC, is that it is informed by that experience. However, the importance of variables such as credit, house prices, interest rates etc was well understood in academic discussion prior to the GFC (see for example, Kaminsky and Reinhart [1999]).

the upper quartile of sovereign bond spreads among euro area countries are also included.[7] Variables relating to the United States are also considered as potential explanatory variables of downturns in Canada.

13. The explanatory variables enter the equations with the minimum lag which is appropriate given both the horizon at which a downturn is being forecast and the extent of any publication lag in that explanatory variable (Table 2, third column). Taking the perspective of a point in time somewhere near the end of the current quarter and designating that quarter as Q_1,[8] then the latest data that is published for the previous quarter, Q_0, is likely to include GDP, industrial production and unemployment. Then if these data are included as explanatory variables to forecast a downturn in quarter Q_n (where n =1, 2 …9), then they should enter with a lag of n quarters. Conversely, some other indicators, mostly relating to credit or international aggregates, will only be available up to quarter Q_{-1} or even $Q_{-2,}$ in which case they would enter the same equations with a with a lag of (n+1) or (n+2) quarters, respectively. Finally, some variables, such as interest rates, oil prices or business surveys, which are available at a higher frequency (daily or monthly) and have a timelier publication, may be almost complete for the current quarter and these variables are included in the equations predicting a downturn in quarter Q_n with a lag of (n-1). For these latter variables, the implicit assumption is that an interpolation of the final weeks of the quarter will be sufficient to provide an accurate representation of the full quarter.

14. A variety of functional forms, relating to different time horizons, are tested for most explanatory variables, including the growth rate over the previous quarter, the previous four quarters, the previous three years or the previous five years. Another set of functional forms, intended to capture a point of inflexion, by taking the difference between a short-term growth rate (such as the quarter-on-quarter growth rate) and a long-term growth rate (such as the average five-year growth rate) are also included. The expected sign on the variable -- the realisation of which is a condition of that variable being selected –varies according to the horizon over which it is being computed (Table 2, final two columns). For example, a strong *positive* growth rate in real house prices over the previous five years as well as a sharp *fall* over the previous quarter might both signal the increased likelihood of a downturn. For functional forms intended to capture a point of inflexion, the “short-term” sign is considered to be the appropriate sign restriction (usually a negative sign restriction, so that a sudden fall after a long period of strong growth increases the downturn risk).

15. Both in estimation and out-of-sample evaluation, the equations use the latest vintage of data rather than the vintage of data that would have been available in 'real time'. Partly this is a practical issue because of the complexity of accessing two different data sets for every year over which the analysis is conducted. Moreover, it may not make a lot of difference to the results as many of the explanatory variables used (for example, interest rates, equity prices, house prices, PMI indicators etc) are rarely, or never, revised. GDP numbers do get revised, sometimes by a lot, but GDP is being used to define the downturn dummies and so it is less likely that the timing and duration of downturns gets substantially revised.

[7] The upper quartile of euro area sovereign bond spreads relative to Germany is measured for nine-euro area countries for which there is data going back to 1980. The measure is normalised, by subtracting a three-year moving average, to create a series which is more consistent over time on the grounds that prior to the creation of the single currency, sovereign bond spreads were more volatile.

[8] Such a perspective is relevant because the intention is for these models to inform the forecasts that are published in the OECD’s *Economic Outlook*, which are published end-May/early June and end-November/early December, so towards the end of the second and fourth quarters of the year, respectively.

2.4. Treatment of the pandemic period

16. For the purposes of the estimation, the declines in GDP associated with the COVID pandemic are not recognised as a downturn because the origins are not financial, as noted earlier. On the other hand, the pandemic was associated with sharp movements in business cycle variables such as capacity utilisation, GDP and industrial production and so not recognising the pandemic as a downturn, then risks prejudicing the subsequent inclusion of these variables in the model equations. The *ad hoc* solution that has been adopted here is to create a pandemic dummy (that is zero during the pandemic downturn and unity elsewhere) that is interacted only with business cycle variables, which should have the effect of ignoring the predictions of the business cycle variables over the pandemic period.

3. The algorithm

17. This section describes the rules underlying the model selection algorithm, a summary of the explanatory variables that are actually selected as well as a modification to the prediction rules if the economy is known to be in a downturn.

3.1. Rules for model selection

18. An algorithm, "DoomBot", is employed to select the 'best' model for each horizon and country as the estimation sample period is extended, from the pool of potential explanatory variables described in the previous section. The variable selection relies on a systematic testing of all potential combinations of explanatory variables, with the final selection based on goodness-of-fit criteria, but subject to the structural restrictions on the signs and lags that ensure that the model has a meaningful economic interpretation and that there is some degree of consistency across models at different horizons.

19. In order to check its out-of-sample performance, the algorithm is run for each of the 20 OECD countries every two quarters from 2005Q1 to 2023Q1, so that each point of re-estimation roughly corresponds with an information set that would have been available at the time of the publication of successive Economic Outlooks from the Spring 2005 edition onwards. The algorithm is run separately for each country and follows three steps:

- **Step 1**: To limit the number of potential equations, a first selection of explanatory variables is performed by choosing the 20 variables (transformed and appropriately lagged according to the forecast horizon) for each horizon, which have the highest correlations with a quarterly dummy signifying a downturn quarter, subject to the correlation being "correctly signed" (where the correct sign is based on Table 1).
- **Step 2**: All possible combinations of the variables selected in step 1 are then estimated. The maximum number of variables that may enter an equation is set to four, to limit the number of combinations.[9] Equations where the variables have a correct sign and are statistically significant at the 1% threshold are retained. If less than ten equations are selected at a particular horizon, the threshold is raised by 1 percentage point increments, up to a maximum of 10%, until ten equations have been selected at each horizon.
- **Step 3**: The final step consists in deciding which combination of equations at the 9 different forecast horizons to choose in order to constitute a model. The three equations with the highest accuracy, judged according to the AUROC statistic (Box 1), at each of the nine forecast horizons are combined in all potential combinations, which represents 3^9 (or about 20,000) potential models.

[9] Tests have been performed to allow a maximum of five variables, but without finding much, or any, improvement in predictive performance.

Each of those models consist of equations respecting the structural constraints and having the highest accuracy, so the final model selection focuses on three other desirable properties:

- An "*early warning*" score of each equation is based on the ability to predict the first or second quarter of any downturn, since being able to predict the start of any downturn is likely to be more useful to policymakers. This score is computed as the average fitted probabilities of the two first quarters of historical downturns from each of the 9 equations.
- A "*consensus*" score for each equation, to penalise the selection of an outlier equation with a forecast that is very different from the average of all the other equations selected in step 2. This is represented by a score from 0 to 1, computed as the absolute difference of the equation forecast from the consensus across all potential equations, subtracted from 1.0. The score for the model is the simple average of the "consensus" score over the 9 equations.[10]
- A "smoothness" score for each model, to favour forecast probabilities that don't fluctuate greatly from quarter-to-quarter, computed as the sum of the absolute squared difference between predictions at adjacent quarters, subtracted from 1.0.

20. These three scores are then normalised and combined with equal weights[11] for each of the potential models, and the model with the highest score is selected as the final preferred model.

3.2. A summary of the explanatory variables selected

21. The variables selected depend on the horizon at which the downturn risk is being assessed (Figure 2 and Figure 3), where the following analysis relates not just to the models estimated on the most up-to-date sample period, but rather over all samples, from a first sample ending in 2005 Q2 to that ending in 2023 Q2. For the immediate quarter, business sector variables – survey measures of capacity utilisation, industrial production, (lagged) GDP and unemployment – account for about 30% of the variables selected, but much less at longer horizons. This perhaps reflects the fact that many of these variables are directly related to activity so that if they are strongly signalling a downturn it is quite likely that one is in progress. Over all horizons, credit and house prices are among the most frequently selected variables: domestic credit and house price variables account for 20-30% of variables selected at all horizons; and international measures of credit and house prices account for between 20-30% at all horizons. Other financial variables include equity prices, accounting for 15-20% of variables selected at horizons between one and two quarters, as well as interest rates, mostly measured by the slope of the yield curve, which account for up to 10% of the variables selected. Beyond a horizon of the first two quarters, oil prices account for about 10% of the variables selected.

22. The variables selected are balanced in terms of their domestic versus international scope. Domestic business cycle variables make up for about 15% of the total variables selected across countries and simulations; domestic financial variables for over 40%; real oil prices represent 10% and other international variables 35% of the total variable selection.

23. The full range of functional forms is reflected in the selections underlining the importance of considering a range of dynamics: short-term changes (over one or four quarters) make up 15% of the total

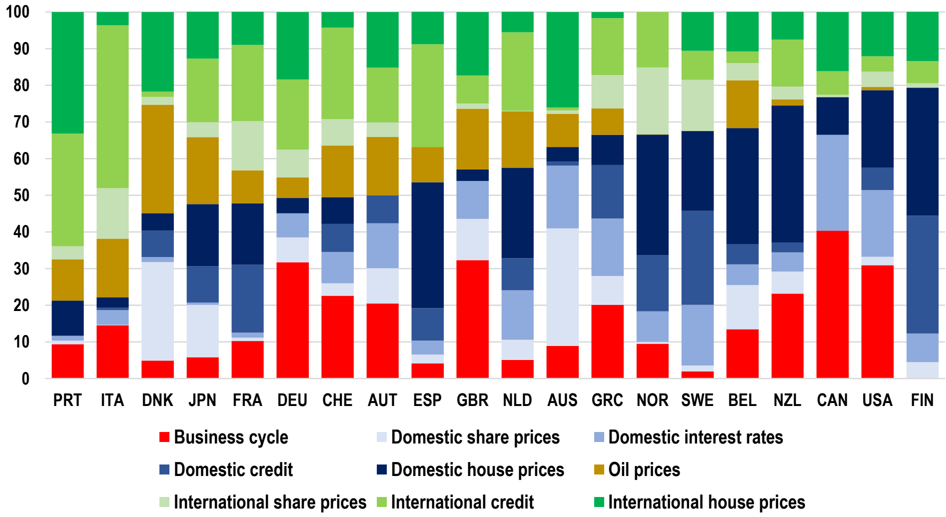
[10] This approach to giving weight to the consensus is preferred to averaging predictions across several equations to derive the preferred prediction because it is then easier to decompose the contributions and so explain the prediction from an individual equation. Also, testing on a number of individual countries suggests that any improvement in performance, as measured by the AUROC score, is negligible from using an average of the best-performing equations compared to the approach adopted here.

[11] Each of the three scores are first normalised by subtracting the average score across all models and dividing by the standard deviation across all models. The final score combined the three normalised scores, giving equal weight to each criterion. Future work could investigate the effect of varying the weights across the different criteria.

functional form choice; functional forms intended to capture an inflexion between short-term and long-term growth for 30%; series expressed in levels (the yield curve slope and euro area interest spread) for 7%; and long-term changes (over three- or five-years) for a bit less than half the selected variables.

Figure 2. Selection of explanatory variables by country

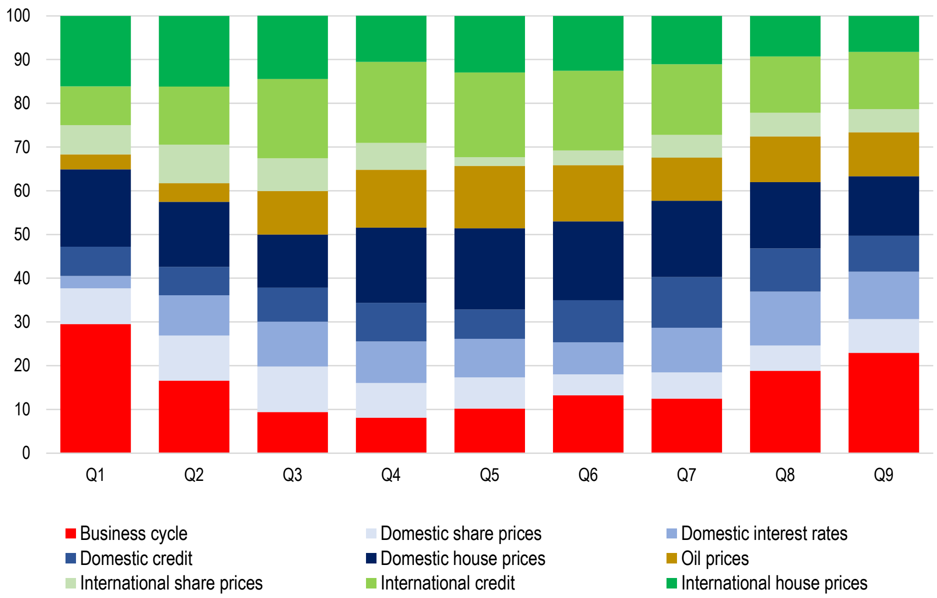
Share of all explanatory variables chosen across all horizons and vintages of model, percent



Note: The chart shows the shares of variables selected by broad categories and country, ignoring the functional form of the variables. Countries are ranked according to the share of domestic rather than international explanatory variables. "Business cycle" variables include the unemployment rate, the capacity utilisation, industrial production and GDP per capita. "Interest rate" explanatory variables include the slope of the yield curve, a measure of government bond interest rate spreads across the euro area and the change in short-term interest rates.

Figure 3. Selection of explanatory variables by forecast horizon

Share of all explanatory variables chosen across countries and vintages of model, percent



Note: The chart shows the shares of variables selected by broad categories and horizon of forecast, ignoring the functional form of the variables. "Business cycle" variables include the unemployment rate, the capacity utilisation, industrial production and GDP per capita. "Interest rate" explanatory variables include the slope of the yield curve, a measure of government bond interest rate spreads across the euro area and the change in short-term interest rates.

3.3. A modified prediction rule when the economy is already in a downturn

24. The method of forecasting the probability that a future quarter will be a downturn differs when, from the perspective of when the forecast is being made, the economy is already known to be in a downturn. The intuition behind this alternative approach is that while a pronged period of financial pressures (for example as represented by a long period of sustained growth in credit or house prices) may correctly signal the onset of a downturn, these same variables may be less helpful in predicting how long the downturn will continue once it is clear that a downturn is underway. Instead, if it is known from the perspective of the quarter in which the forecast is being made that previous quarters were already in a downturn,[12] then a simpler rule is used, based on the length of the current downturn already experienced compared with the length of previously experienced downturns.

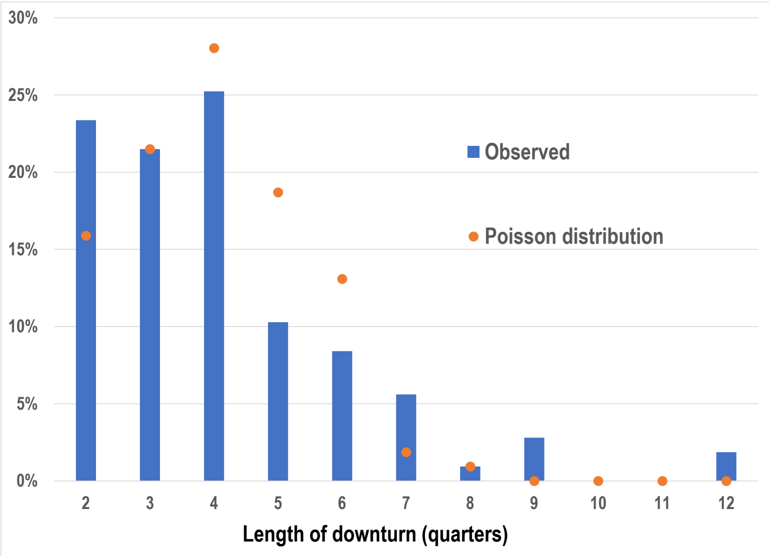
25. More specifically, the method of projecting the length, L quarters, of a downturn assumes that (L-2) has a Poisson distribution with a country-specific mean determined as the average length (minus 2) of previously completed downturns. The adjustment by "-2" is because a downturn cannot be less than 2 quarters long, so that the length of the downturn in excess of two quarters is assumed to have a Poisson distribution. A comparison of the distribution of the length of downturns across all countries over the entire sample (1980-2022) with a Poisson distribution having mean equal to (L*-2), where L* is the average length

[12] In order to recognise the current quarter is a downturn requires that there has been at least two quarters of negative GDP per capita growth and the cumulative loss in GDP per capita exceeds the relevant country-specific threshold (see section 2).

of downturns across all countries, suggests that the Poisson distribution is indeed a reasonable approximation (Figure 4). The main exception is Spain which experienced a downturn episode associated with teh euro area crisis which lasted 12 quarters. Note, however, when computing out-of-sample probabilities the Poisson distribution uses the country-specific average available to that date, rather than the average across all countries over the entire sample.

Figure 4. The Poisson distribution as an approximation of the length of a downturn

The frequency distribution of the length of a downturn for all countries since 1980, percentage of all downturns

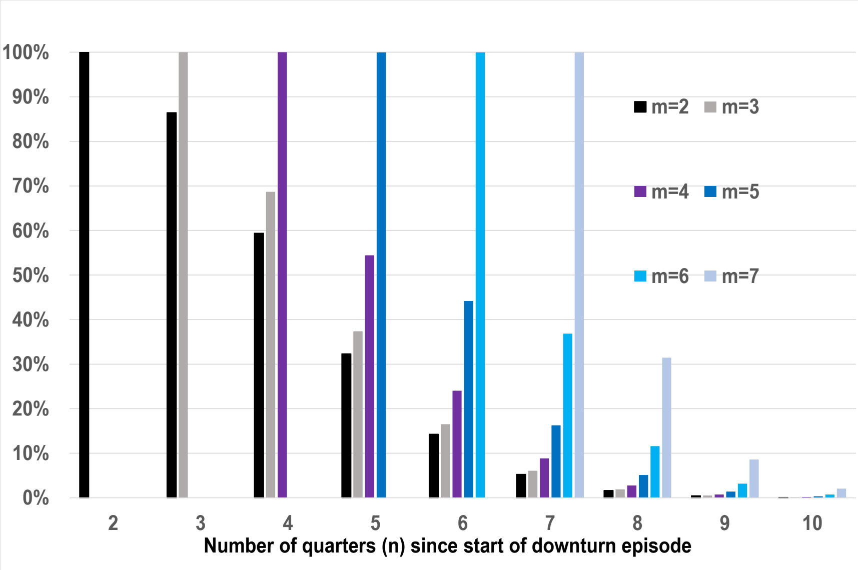


Note: The chart compares the frequency distribution of the length of downturns across all countries in the study over the full sample 1980-2022 with a Poisson distribution with mean equal to (L*-2), where L* is the mean downturn length across all countries over the full sample.

26. The Poisson distribution is assumed to represent the *unconditional* probability distribution of the length of a downturn. However, for the purposes of this application it is necessary to compute a *conditional* probability distribution that the nth quarter after the start of a downturn episode is a downturn quarter, given that the downturn has already lasted m quarters (n>=m>=2), P(L>=n | L>=m). Following a simple manipulation using Bayes theorem, this is easily shown to be equal to P(L>=n) / P(L>=m) and is illustrated in Figure 5 for different values of n and m under the assumption that the average length of all downturns is four quarters. Thus, for the example represented in Figure 5, if it is known that the downturn has already lasted 2 quarters, then the probability that the 4^{th} quarter is also a downturn is nearly 60%, whereas if the downturn has already lasted 4 quarters the probability that the sixth quarter is also a downturn is under 25%.

Figure 5. The conditional probability distribution of the length of a downturn

The probability that the nth quarter is a downturn given that the downturn has already lasted m quarters



Note: The figure shows the conditional probability distribution that the nth quarter following the start of a downturn episode is also a downturn given the downturn episode is known to already have lasted m quarters, assuming the unconditional probability distribution of the length of a downturn in excess of 2 quarters can be represented by a Poisson distribution with a mean of 2 (implying that the mean length of a downturn is 4 quarters), where the latter assumption is made here for illustrative purposes and in application the mean length of a downturn is country-specific and calculated from past experience.

4. Assessing performance

27. This section analyses the quality of fit of the probit models, both in terms of their full in-sample performance as well as out-of-sample performance, but with an emphasis on the latter, using standard performance metrics (Box 1). For the purpose of the out-of-sample evaluation, the period from 1980Q1-2004Q4 is treated as the training sample, with the timing of successive quasi-real time updates of the models from 2005Q2 onwards then corresponding approximately with successive biannual publications of the *OECD Economic Outlook*, which takes place towards the end of the second and fourth quarters of each year. Thus, the information that would have been available at the time of publication of each successive *Economic Outlook* includes the data that is used for each successive update of the algorithm, so enabling a comparison between the predictions of the algorithm and those in the *Economic Outlook*.

Box 1. Evaluating the performance of binary classification models

This box describes two metrics, the Area Under the Receiver Operating Characteristic (AUROC) and the F-score, which are commonly used in machine learning for evaluating the performance of binary classification models.

The F-score is a metric used to evaluate the performance of a binary classification model based on 'precision' and 'recall', which are computed from the four confusion matrix concepts: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Precision measures the proportion of true positives among all predicted positives, while recall measures the proportion of true positives among all actual positives. The F-score is the harmonic mean of precision and recall, taking a value of between zero and one, and is computed as follows:

F-score = 2 * TP / (2 * TP + FP + FN)

The probit models reported in this paper predict the probability of an event (a downturn), so to compute the F-score these predictions need to be translated into a binary classification of either a positive or negative occurrence, which is achieved by assuming that if the probability exceeds a specific threshold the prediction is classified as positive and otherwise as negative. In this case the threshold is set at the share of all quarters in the sample that are classified as downturns (typically about 15%). The F-score is thus specific to the threshold chosen, ranging from 0 to 1, with a higher value indicating better performance.

A conceptual advantage of AUROC is that it does not depend on the arbitrary choice of a threshold, rather it measures the ability of the model to distinguish between positive and negative classes by plotting the true positive rate (TPR) against the false positive rate (FPR) at different classification thresholds. The AUROC is then the computation of the area under this curve. The AUROC ranges from 0 to 1, with a higher value indicating better performance. Although there are no strict criteria, an AUROC score in excess of 0.9 is usually regarded as very good; a score of between 0.8 and 0.9 as good; a score between 0.7 and 0.8 as acceptable; and a score of between 0.5 and 0.7 as poor. An AUROC score of 0.5, implies the model ranks a random positive example higher than a random negative example 50% of the time, suggesting the model is basically worthless, as its predictive ability is no better than random guessing.

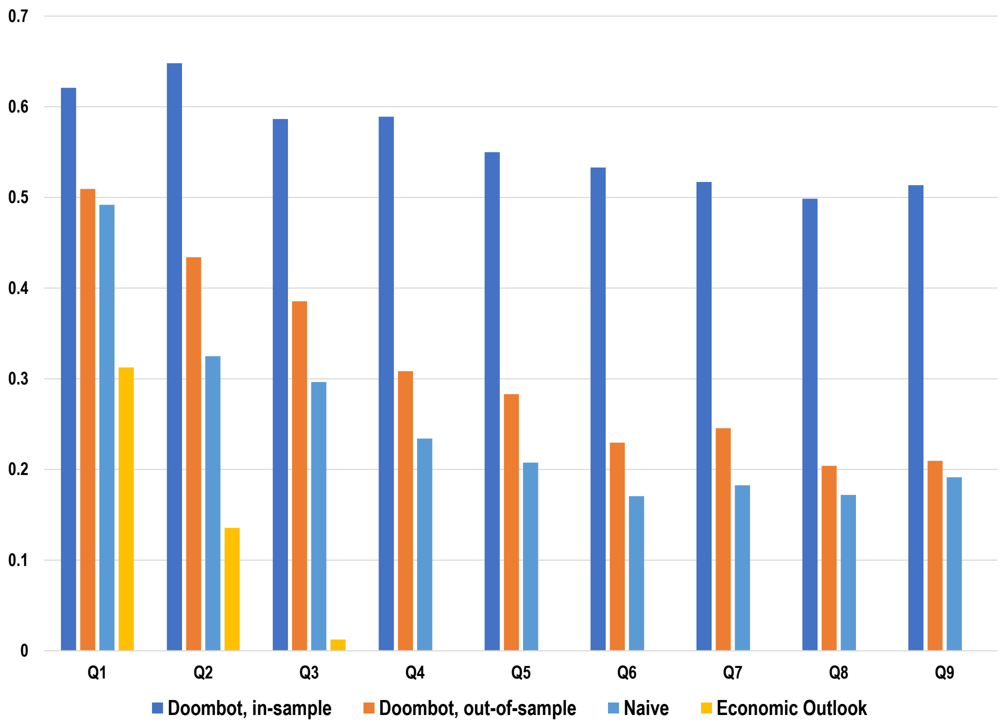
4.1. *Comparison of Doombot with naïve forecasts and the Economic Outlook*

28. Two benchmarks for comparison are the *Economic Outlook* forecasts and a naïve forecast, where the latter is constructed by assuming that if GDP growth in the preceding quarter is negative then the quarters over the entire (7- or 9-quarter) forecast horizon are assumed to be downturns, otherwise they are all assumed to be non-downturn quarters. There is a clear ranking of predictions according to the F-score criteria (Figure 4, Box1), with all predictions tending to score lower as the forecast horizon is extended: the in-sample Doombot predictions score highest at all horizons and deteriorate least as the forecast horizon is extended; the out-of-sample Doombot predictions rank second at all horizons and more clearly deteriorate as the forecast horizon is extended, with the margin relative to naïve forecasts also

declining at longer horizons;[13] the naïve forecast always beat OECD forecasts, with the latter particularly poor beyond a horizon of the immediate two quarters. The poor performance of OECD forecasts in predicting future downturns is consistent with many studies documenting the failure of forecasters to predict future recessions (Loungani, 2001; Abreu, 2011; Fildes and Steckler, 2002; Pain and Lewis, 2014; An et al, 2018) and is perhaps explained by a tendency to mean reversion when forecasting GDP.

Figure 4. F-score by forecast horizon

Comparing Doombot predictions with naïve forecasts and Economic Outlook forecasts, 2005Q2-2023Q1



Note: The F-score is explained in Box 1. The naïve forecast rule predicts downturns over the entire projection horizon if the preceding quarter has negative GDP growth, and non-downturns otherwise.

4.2. Comparison of Doombot out-of-sample and in-sample performance

29. The full in-sample performance of the Doombot forecasts is very good based on the AUROC scores (Box 1), which when averaged across all 20 countries exceeds 0.9 for the forecasts up to 5 quarters ahead, and dips just below 0.9 for horizons beyond that (Table 3, LHS panel). Moreover, this good in-sample performance is a feature of a clear majority of countries at most horizons (further details of in-sample performance at different horizons for each country is shown in Annex A).

30. In terms of out-of-sample performance, again averaging across countries, the highest score exceeds 0.8 for the immediate quarter, but then mostly has an acceptable performance with the score

[13] The F-score likely flatters the performance of the naïve forecast rule because of the proximity of the GFC and euro area crises, because initial quarters of negative growth during the GFC are projected as downturns by up to 9 quarters, so spanning the period of the euro area crisis. This is borne out by the difference between the F-scores for euro area and non-euro countries, where the F-score for the former is up to 0.3 higher than for the latter (with the biggest difference at short horizons), and on average more than 0.1 higher at all horizons.

exceeding 0.7 in all but 2 quarters (Table 3, RHS panel). Underlying this average score is a wider variation in performance across different countries, with one quarter of all countries having a good performance (an AUROC score exceeding 0.8), another quarter having an acceptable performance (score between 0.7 and 0.8), but with half of all countries having a poor performance (score of less than 0.7). To better understand the reasons for these lower scores, and why they may arguably understate the usefulness of the models, the following sub-sections examine in more detail the time series of the out-of-sample performance, focussing on the two major downturn episodes during the evaluation period, namely the Global Financial Crisis and euro area crisis.

Table 3. The AUROC score across countries

Comparing in-sample and out-of-sample Doombot performance, for period 2005Q1-2023Q1

In-sample

Country	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Average
AUS	0.94	0.97	0.96	0.92	0.86	0.95	0.94	0.93	0.95	**0.94**
AUT	0.87	0.93	0.91	0.91	0.92	0.84	0.84	0.82	0.78	**0.87**
BEL	0.98	0.93	0.92	0.95	0.80	0.95	0.92	0.77	0.86	**0.90**
CAN	0.97	0.83	0.76	0.69	0.89	0.77	0.70	0.72	0.77	**0.79**
CHE	0.93	0.83	0.91	0.94	0.88	0.89	0.89	0.89	0.86	**0.89**
DEU	0.93	0.97	0.96	0.98	0.96	0.82	0.93	0.83	0.82	**0.91**
DNK	0.94	1.00	0.97	0.92	0.94	0.95	0.94	0.84	0.85	**0.93**
ESP	0.97	0.98	0.95	0.92	0.94	0.93	0.95	0.95	0.93	**0.95**
FIN	0.92	0.92	0.96	0.81	0.88	0.82	0.83	0.74	0.72	**0.84**
FRA	0.88	0.92	0.94	0.91	0.91	0.88	0.79	0.84	0.90	**0.89**
GBR	1.00	0.99	1.00	1.00	1.00	0.96	0.82	0.83	1.00	**0.96**
GRC	0.94	0.94	0.98	0.94	0.90	0.89	0.90	0.92	0.90	**0.92**
ITA	0.96	0.96	0.94	0.94	0.96	0.91	0.93	0.84	0.88	**0.92**
JPN	0.96	0.89	0.85	0.91	0.93	0.87	0.89	0.84	0.89	**0.89**
NLD	0.98	1.00	0.98	0.98	0.97	0.96	0.95	0.92	0.90	**0.96**
NOR	0.98	0.95	0.95	0.91	0.95	0.97	0.88	0.86	0.92	**0.93**
NZL	0.94	0.90	0.93	0.89	0.86	0.91	0.86	0.84	0.93	**0.90**
PRT	0.99	0.97	0.97	0.89	0.90	0.89	0.90	0.91	0.90	**0.92**
SWE	0.90	0.90	0.92	0.93	0.92	0.81	0.86	0.89	0.82	**0.88**
USA	0.88	0.85	0.97	0.95	0.93	0.95	0.92	0.93	0.89	**0.92**
Average	**0.94**	**0.93**	**0.94**	**0.91**	**0.92**	**0.90**	**0.88**	**0.86**	**0.87**	**0.91**

Out-of-sample

Country	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Average
AUS	0.67	0.93	0.95	0.85	0.71	0.82	0.92	0.93	0.96	**0.86**
AUT	0.86	0.70	0.66	0.59	0.72	0.56	0.56	0.66	0.50	**0.65**
BEL	0.79	0.50	0.57	0.67	0.56	0.59	0.78	0.56	0.73	**0.64**
CAN	0.89	0.52	0.77	0.68	0.84	0.58	0.64	0.58	0.76	**0.70**
CHE	0.98	0.88	0.92	0.68	0.70	0.54	0.85	0.71	0.84	**0.79**
DEU	0.73	0.76	0.98	0.99	0.76	0.69	0.82	0.84	0.73	**0.81**
DNK	0.86	0.87	0.71	0.84	0.89	0.87	0.84	0.63	0.74	**0.81**
ESP	0.94	0.92	0.91	0.92	0.81	0.58	0.59	0.80	0.75	**0.80**
FIN	0.71	0.60	0.65	0.56	0.61	0.55	0.52	0.51	0.63	**0.59**
FRA	0.68	0.61	0.63	0.60	0.65	0.66	0.87	0.74	0.58	**0.67**
GBR	0.96	0.78	0.82	0.92	0.75	0.80	0.72	0.50	0.53	**0.75**
GRC	0.85	0.89	0.79	0.69	0.56	0.77	0.80	0.73	0.71	**0.75**
ITA	0.90	0.86	0.66	0.58	0.82	0.76	0.63	0.60	0.58	**0.71**
JPN	0.65	0.58	0.56	0.66	0.62	0.62	0.91	0.67	0.79	**0.67**
NLD	0.86	0.76	0.70	0.60	0.78	0.58	0.54	0.63	0.57	**0.67**
NOR	0.92	0.78	0.99	0.83	0.90	0.98	0.93	0.66	0.87	**0.87**
NZL	0.91	0.58	0.51	0.71	0.62	0.53	0.73	0.53	0.91	**0.67**
PRT	0.91	0.83	0.69	0.60	0.62	0.53	0.50	0.57	0.61	**0.65**
SWE	0.74	0.65	0.51	0.69	0.57	0.61	0.56	0.66	0.56	**0.62**
USA	0.94	0.69	0.52	0.80	0.81	0.63	0.81	0.76	0.72	**0.74**
Average	**0.84**	**0.73**	**0.73**	**0.72**	**0.72**	**0.66**	**0.73**	**0.66**	**0.70**	**0.72**

Note: The shading of the table cells provides a guide to the performance of the probit models for each country over different horizons: an AUROC score of between 0.5 and 0.7, shaded red, indicates a poor performance; a score of between 0.7 and 0.8, shaded yellow, indicates an acceptable performance; and a score above 0.8, shaded green, indicates a good performance.

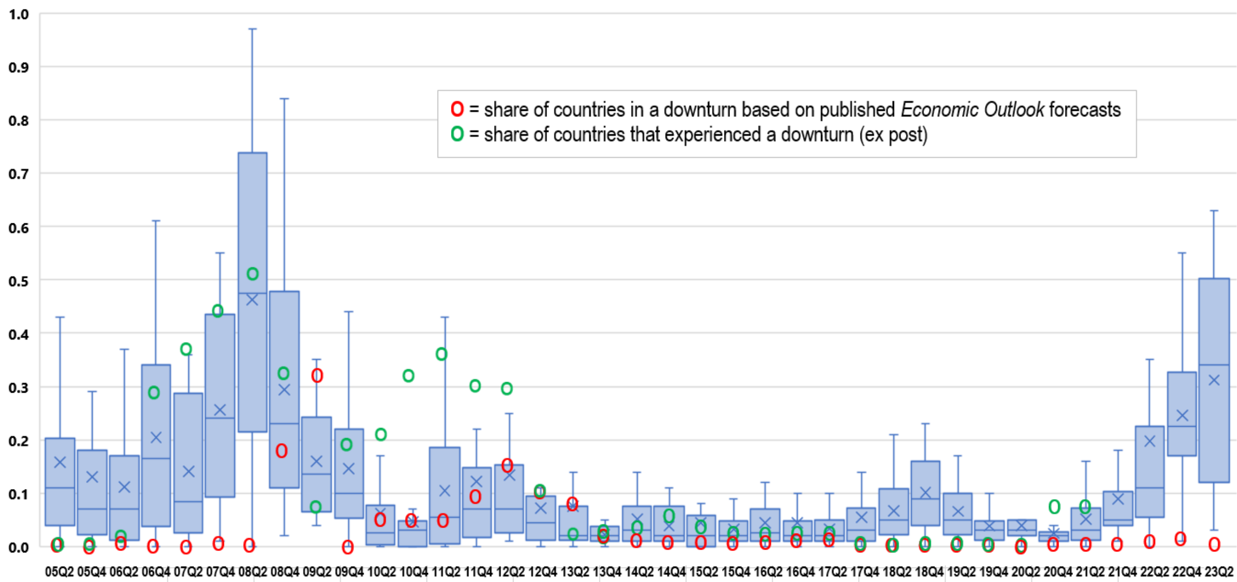
31. The out-of-sample performance over time is summarised across all countries in a box and whiskers plot (Figure 5), where the dating on the x-axis corresponds to the time at which the forecast is made. For example, the 2008 Q2 ("08Q2") observation summarises the distribution of Doombot downturn probabilities across all 20 countries for the (7) quarters, 2008Q2-2009Q4, covered by the June 2008 *Economic Outlook*. More detailed charts showing the evolution of out-of-sample predictions for each country separately are shown in Annex B. For comparison purposes, the red circles, superimposed on the box and whiskers plot, show the share of forecast quarters for all 20 OECD countries that were predicted to be in a downturn according to the corresponding published EO projections,[14] whereas the green circles show the actual

[14] A common feature of OECD forecasts, and indeed most other macroeconomic forecasts, is that beyond the current year, GDP projections are characterised to some degree by a reversion to average historical growth (Turner, 2016). A corollary is that it is almost never the case that published forecasts include the possibility that an economy is in a downturn more than 4 quarters into the future. Thus, a comparison of downturn probabilities with published forecasts

share of quarters that (*ex post*) experienced a downturn over the same horizon. The following features stand out from a cursory examination of the distribution of forecast probabilities: there were widespread and rising downturn probabilities ahead of the GFC; a pick-up in probabilities ahead of the euro area crisis, but on a much more modest scale, particularly given the number of countries that actually experienced a downturn over this period (as indicated by the green circles), which included all 10 euro area countries; and there has been a marked pick-up in probabilities since mid-2022. Each of these episodes is examined in more detail below.

Figure 5. Distribution of out-of-sample downturn probabilities for 20 OECD countries

Average of projected quarters, made at the time of successive publications of the *Economic Outlook*



Note: The box and whiskers plot shows the distribution of out-of-sample Doombot downturn probabilities for 20 OECD countries, where the probability of a downturn for each country is first averaged over each quarter of the corresponding *Economic Outlook* (EO) forecast horizon. The dating of the x-axis corresponds to the quarter in which the EO forecast was published, defining both the dataset available for the predictions and the forecast horizon: for example, "08Q2" corresponds to the timing of the June 2008 EO forecast and covers the period 2008Q2-2009Q4. The box shows the inter-quartile range for the 20 countries; the whiskers the extremes; the "X" is the simple average; and the horizontal bar is the median. The red circles show the share of forecast quarters for all 20 OECD countries that were predicted to be in a downturn according to the published EO projections, whereas the green circles show the actual share of quarters that experienced a downturn over the same horizon. Note for the purposes of this chart, the declines in GDP experienced during the pandemic are not classified as downturns, consistent with the definition of a downturn used elsewhere in this study.

4.3. Out-of-sample performance in predicting the Global Financial Crisis

32. Predicted out-of-sample downturn probabilities were already elevated from projections made from the viewpoint of 2005Q2 (covering a forecast horizon to end-2006), 2005Q4 and 2006Q2 (both covering a forecast horizon to end-2007), with average probabilities for these forecasts across all countries and horizons averaging about 15% (Figure 5). These predictions are virtually all false alarms and so contribute negatively to any scoring of out-of-sample performance because downturn episodes began mostly in 2008. On the other hand, arguably such early warnings should count less negatively because they could have

beyond a horizon of 4 quarters is unlikely to be informative. On the other hand, the difficulty of forecasting volatility beyond the short run is noteworthy and could be viewed as a collective failure of all macroeconomic forecasters.

provided policymakers with more time to take remedial action, which, while it may not have avoided a downturn, could have reduced its severity.

33. Successive predictions made from the viewpoint of 2006 Q4 (covering a horizon to end-2008) to those made from the viewpoint of 2008 Q2 (covering a horizon to end 2009) show increasingly higher downturn probabilities, with the average across all countries and horizons for the latter predictions peaking at a sample high of nearly 50%. These high probabilities coincide with the high incidence of downturns experienced by OECD countries over the corresponding projection horizons (as evidenced by the green circles in Figure 5). By contrast, the *Economic Outlook* projections made over the same horizons all predicted the absence of any downturns (as evidenced by the red circles in Figure 5).

34. Predictions made from the viewpoint of 2009 Q2 (covering a horizon to end-2010) imply a diminishing incidence of downturns, with the average probability across all countries and horizons falling to about 15%. Given that the trough of the GFC for most OECD countries was in the first half of 2009, with most countries experiencing positive growth through 2010, this suggests that at least in aggregate, the algorithm is correctly signalling the start of the recovery phase. In contrast, the *Economic Outlook* projections made at this time implied that the incidence of downturns across all countries and all quarters to end 2010 would be about one-third.

4.4. Out-of-sample performance in predicting the euro area crisis

35. The out-of-sample performance of Doombot in predicting the downturns associated with the euro area sovereign debt crisis is less impressive. Part of the difficulty of identifying the euro area crisis may be that it followed closely on the heels of the GFC: by 2011 Q2 half of the ten euro-area countries in the sample were in a downturn (compared to only one country outside the euro area) and this number rose steadily to the 2012 Q4 when all euro countries were in a downturn (compared to two countries outside the euro area). The out-of-sample Doombot predictions pick up these risks late and only partially: of the predictions made from the viewpoint of 2010 Q2 (covering a horizon to end 2011) only Greece and Spain had significant downturn probabilities (averaging 32% and 14%, respectively, across the forecast horizon); by the time of the predictions made from the viewpoint of 2011 Q2 (covering a horizon to end 2012), Portugal and Spain also had significant downturn probabilities, of 30% and 15%, respectively. However, risks to most other euro area countries, were either signalled later or were absent.

36. The failure of Doombot to pick up more widespread risks to euro area countries, likely reflects the systemic nature of the euro area crisis, which was not well reflected in the historical sample over which the algorithm was estimated. Thus, the systemic nature of the crisis went beyond the trade and financial linkages apparent in previous synchronised downturns, by exposing vulnerabilities in the arrangements underlying the single currency, in particular the absence of any unambiguous lender-of-last resort coupled with the so called ‘doom-loop’ of banks holding large shares of sovereign bonds. These weaknesses were largely a consequence of the single currency arrangements introduced in 1999 and 2002 and so there was little historical experience of such vulnerabilities prior to the euro area crisis.

37. There is, however, some evidence of the algorithm ‘learning’ from the crisis, with a variable capturing euro area sovereign bond spreads being selected much more frequently after the crisis than before. This variable is constructed as the upper quartile of 10-year sovereign bond spreads (with respect to German sovereign bonds) among euro area countries in the sample, which is normalised to account for the generally greater volatility of spreads in the era prior to the creation of the single currency.[15] Prior to the euro area crisis, this spread variable is only selected in the models for two to three euro-area countries,

[15] The upper quartile of euro area sovereign bond spreads is measured for nine euro-area countries for which there is data going back to 1980. The measure is normalised, by subtracting a three-year moving average, to create a series which is more consistent over time on the grounds that prior to the creation of the single currency, sovereign bond spreads were more volatile.

whereas after the crisis it is typically picked up in the models for six to seven euro-area countries. The inclusion of this variable partly explains the improvement in the full in-sample performance relative to out-of-sample performance and should mean that the algorithm is better placed to detect any future vulnerabilities which stem from systemic weakness arising from monetary arrangements in the euro area.

5. Downturn risk predictions made in mid-2023

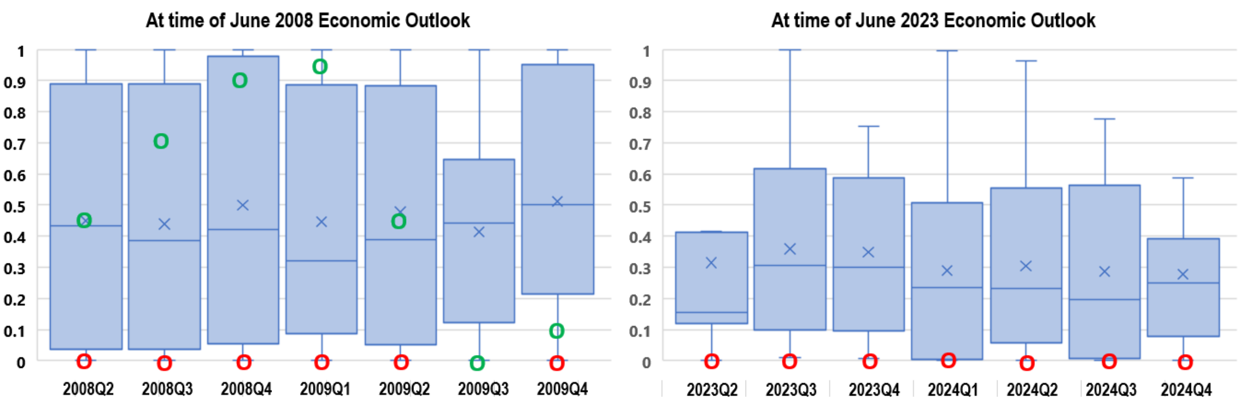
38. This final section considers the latest set of Doombot predictions, made towards the end of 2023 Q2 and consistent with information available at the time of the publication of the June 2023 *Economic Outlook,* which suggest that downturn probabilities are projected to be the most elevated and widespread since the GFC (Figure 5). In contrast, the published *Economic Outlook* projections imply that none of the 20 OECD countries considered here will experience a downturn, although commentary on the central forecasts in the *General Assessment* chapter to the publication does emphasise downside risks, particularly from financial factors:

> "*…major risks to the projections are on the downside. …Significant additional monetary policy tightening may then be required to lower inflation, raising the likelihood of abrupt asset repricing and risk reassessments in financial markets. A related concern is that the strength of the impact from the monetary policy tightening that has already occurred is difficult to gauge after an extended period of very accommodative policy and the speed at which policy interest rates have subsequently been raised. …the impact on economic growth could be stronger than expected if tighter financial conditions were to trigger stress in the financial system and undermine financial stability.*" (OECD, 2023).

39. In comparison with out-of-sample projections made from the perspective of the June 2008 *Economic Outlook*, the current projections are, however, less severe: the average downturn probability across all 20 countries was between 0.4 to 0.5 in June 2008 over the entire forecast horizon, whereas currently the average probability is about 0.3 over the entire forecast horizon (Figure 6).

Figure 6. Comparison of current downturn probabilities with pre-GFC forecasts

Distribution of downturn probabilities among 20 OECD countries



Note: The box and whiskers chart shows the distribution of downturn probabilities among a sample of 20 OECD countries. The LHS panel shows the out-of-sample predictions using information available at the time of the publication of the June 2008 *Economic Outlook*, whereas the RHS panel shows the most recent predictions using information available at the time of the publication of the June 2023 *Economic Outlook*. The red circles show the share of the 20 OECD countries that were predicted to be in a downturn in each quarter according to the published June 2008 *Economic Outlook* (LHS panel) and according to the June 2023 *Economic Outlook* projections (RHS panel), whereas the green circles show the actual share of countries that experienced a downturn in each quarter (for the LHS panel only).

40. The recent predictions are mostly driven by financial developments rather than real activity indicators, which may explain short-run differences with more conventional nowcasting models and with the *Economic Outlook* projections. Details of the latest individual country Doombot equations and projections are provided in Annex C, including a decomposition of the predicted downturn probabilities. In summary, the main drivers of elevated risk probabilities are: international house prices (ten countries); interest rate developments, either the slope of the yield curve or recent sharp increases in short-term rates (ten countries); domestic house prices (eight countries); oil prices (eight countries); and international credit (six countries). On the other hand, two categories of explanatory variable -- business cycle variables and equity prices -- which feature heavily in most country models, especially at shorter horizons, are not contributing significantly to downturn probabilities:

- Business cycle variables (usually survey measures of capacity utilisation or industrial production) feature in two-thirds of country models at short-term horizons of 1-2 quarters, but are currently not contributing significantly to downturn probabilities, except in Canada.
- Falling share prices appear in three-quarters of country models at short-term horizons of 1-2 quarters, but are currently not contributing significantly to downturn probabilities, except in Sweden.

41. Among the G7, average downturn probabilities to end 2024 are between 30 and 50% for all countries except Japan, with the main drivers of downturn risk being as follows:

- United States: the average downturn probability to end 2024 is 30%, with main contributors being the slope of yield curve and domestic house prices;
- Japan: the average downturn probability is only 6%, mostly due to oil prices;
- Germany: the average downturn probability is 29%, mostly due to international developments in house prices and credit as well as oil prices;
- France: the average downturn probability is 34%, mostly due to international developments in credit as well as domestic house prices;
- United Kingdom: the average downturn probability is 30%, mostly due to house prices, the slope of the yield curve and oil prices;
- Italy: average downturn probability is 49%, mostly due to international developments in house prices and credit as well as oil prices;
- Canada: the average downturn probability is 46%, mostly due to survey measures of capacity utilisation at short horizons as well as the slope of the yield curve and US house prices;

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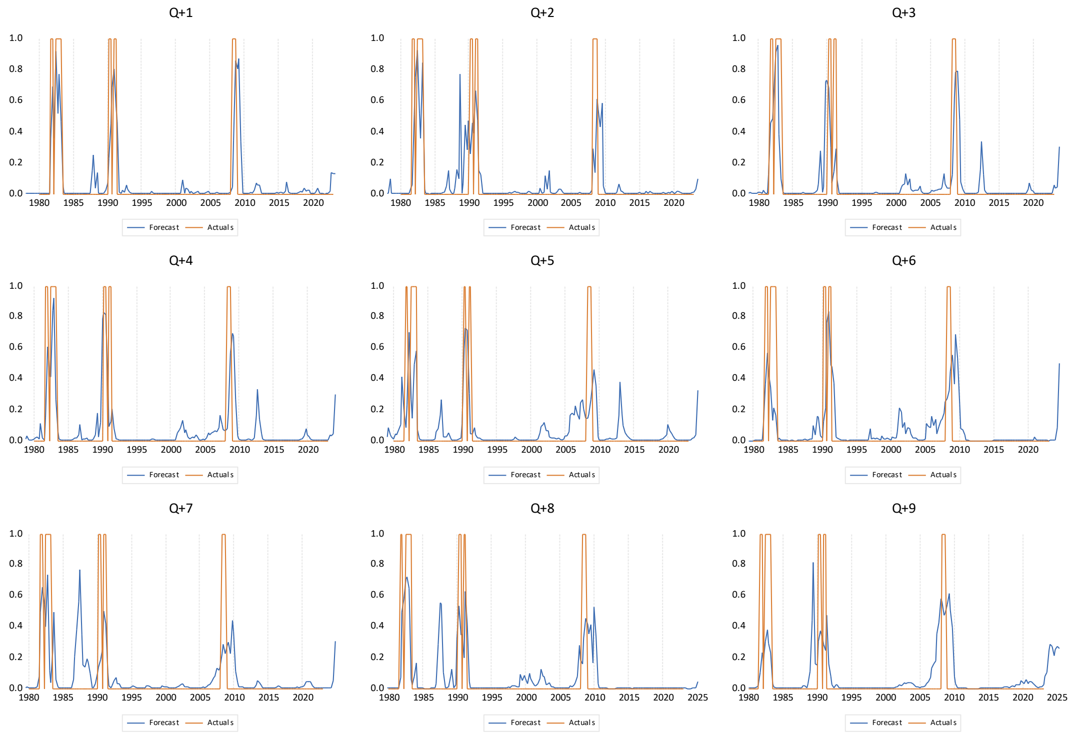
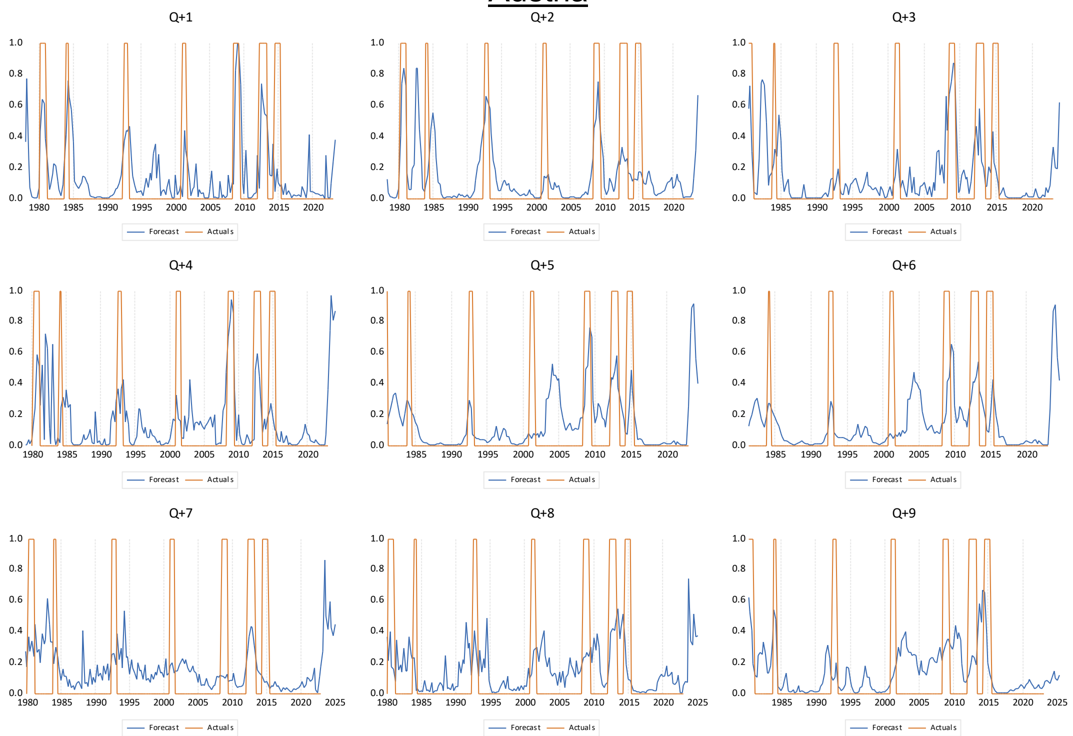
Annex A. Latest equations fitted values ("in-sample" forecasts)

The following sets of charts show the fit of the most recent equations estimated over the period 1980 Q1 to 2023 Q1, for each country and forecast horizon of 1 to 9 quarters (referred to in the charts as "Q+1" to "Q+9"). Predictions are shown to a maximum date of 2025 Q1 for the 9-quarter ahead "Q+9" chart. The blue lines show the in-sample predicted downturn probabilities, as "Forecast", and the orange lines the realised downturn periods, "Actuals".

<u>Australia</u>



Austria



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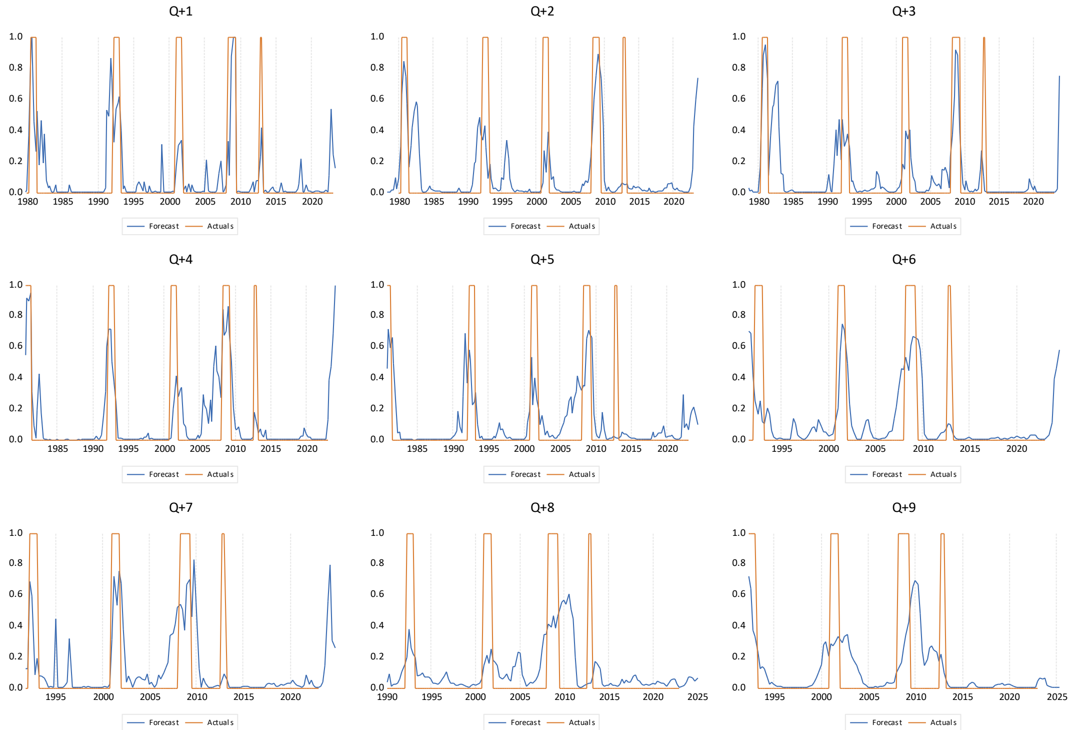
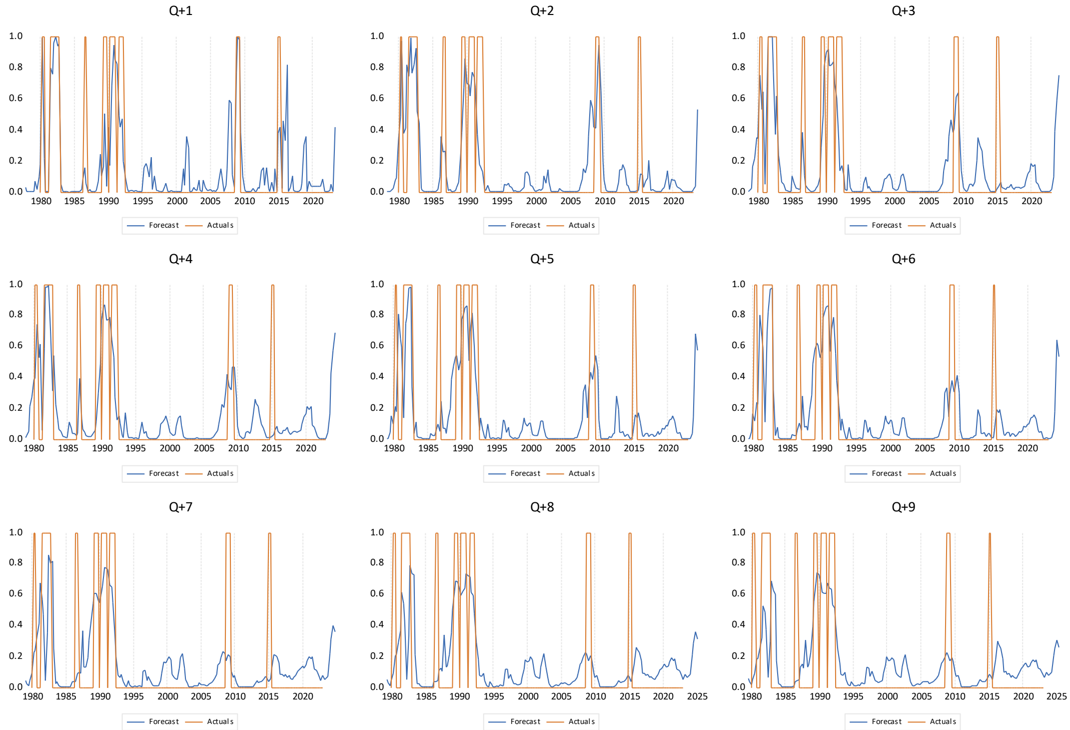
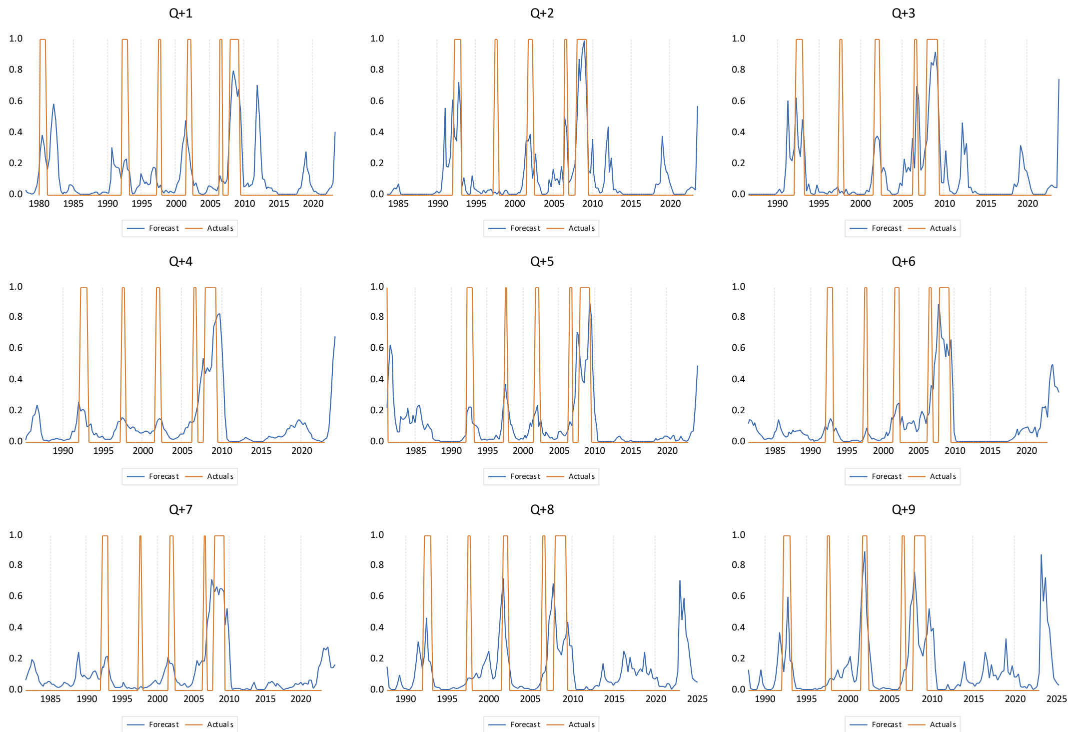


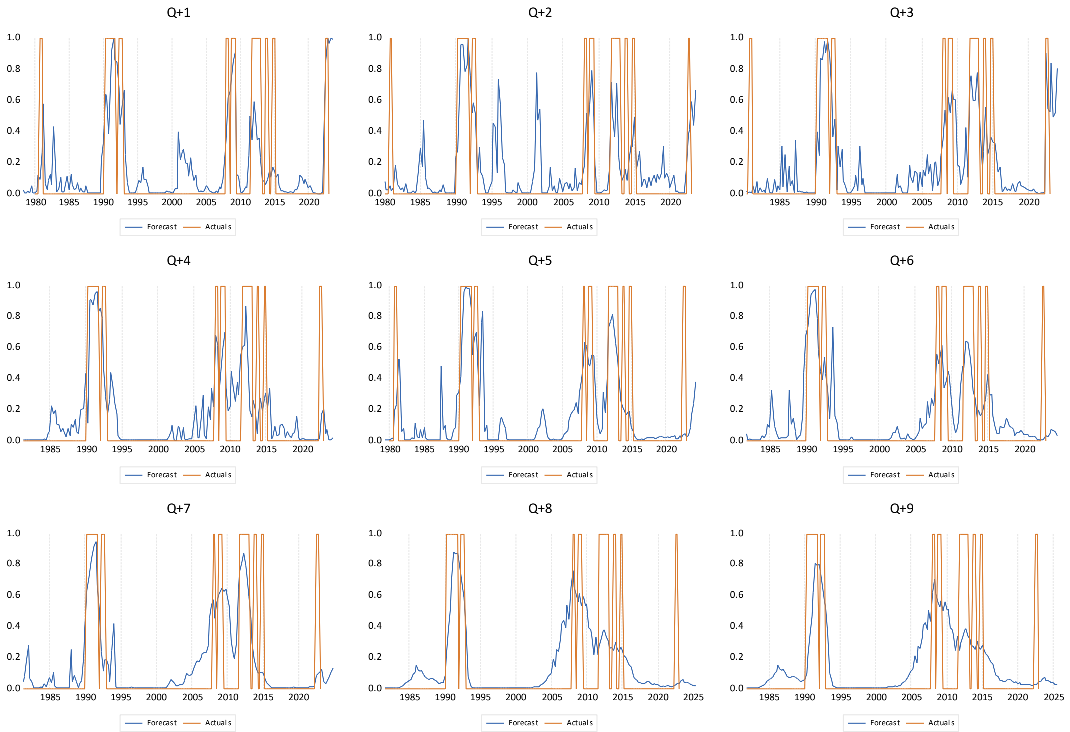
Canada



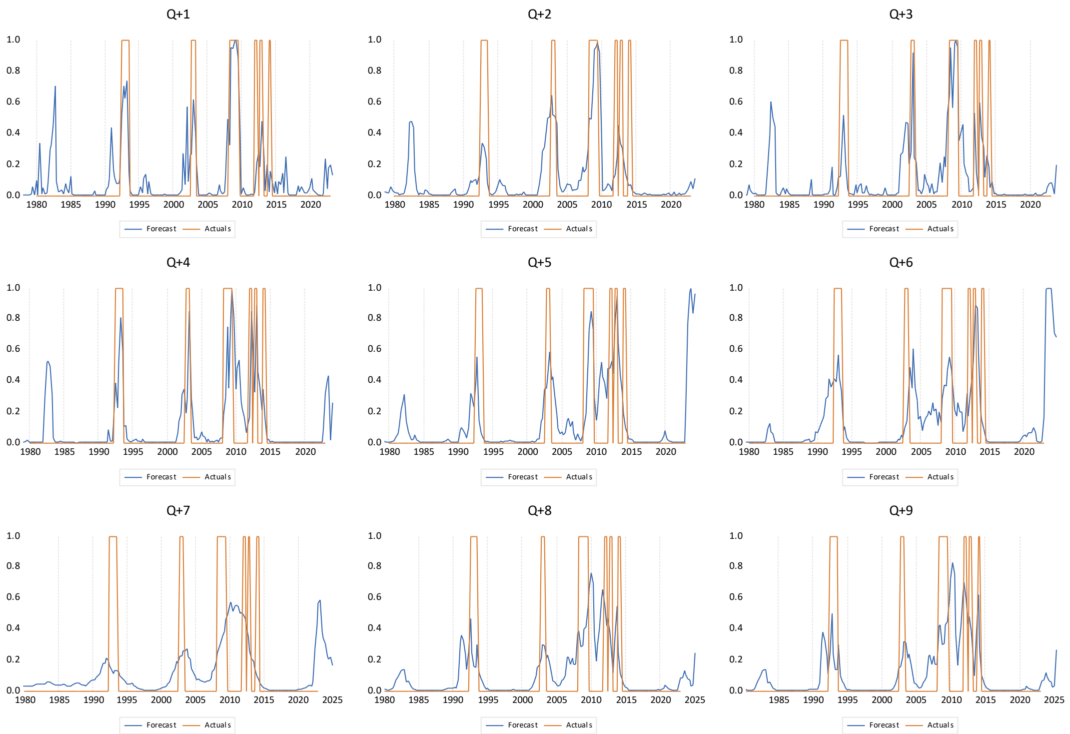
Denmark



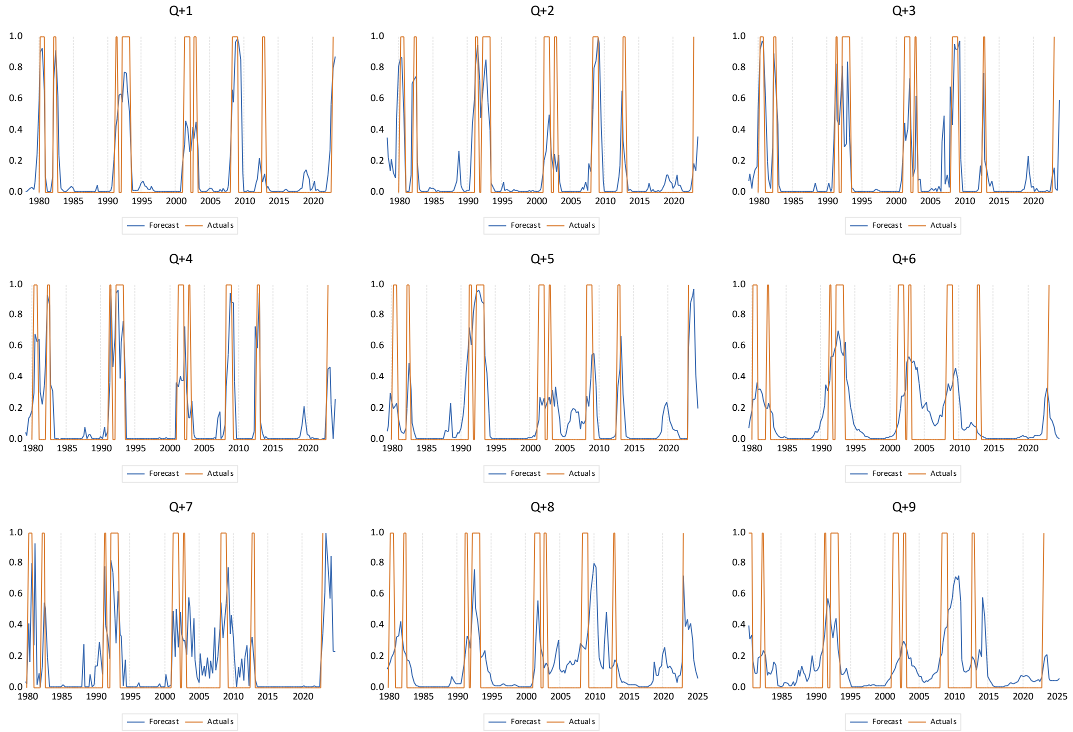
Finland



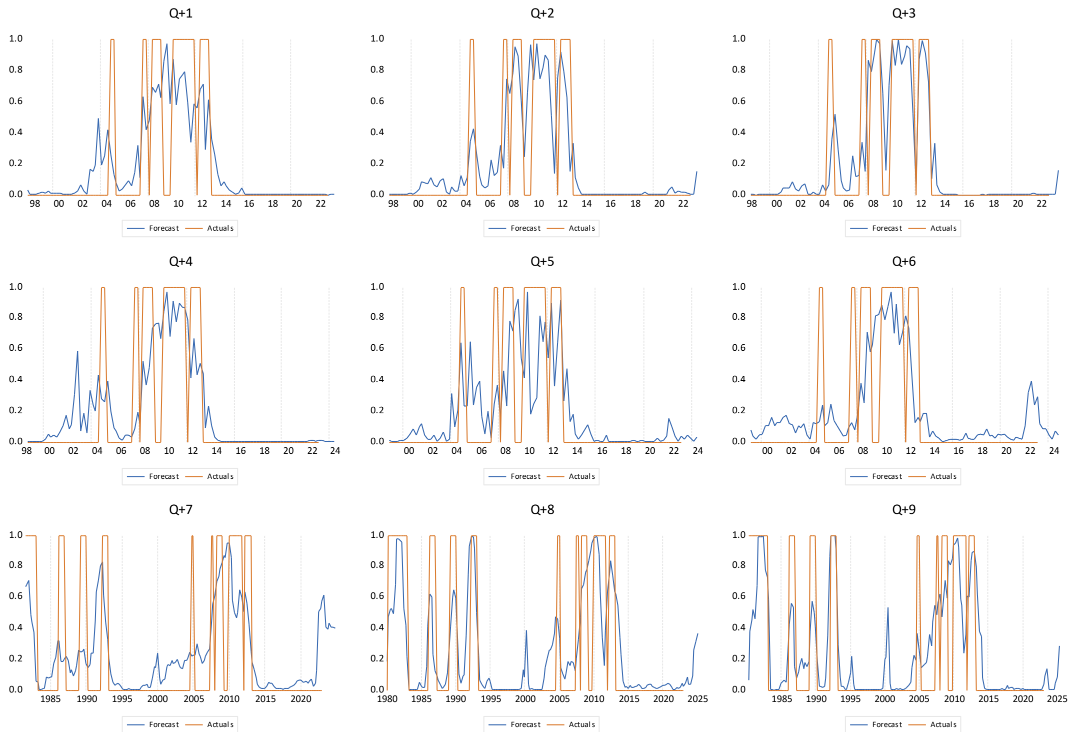
France



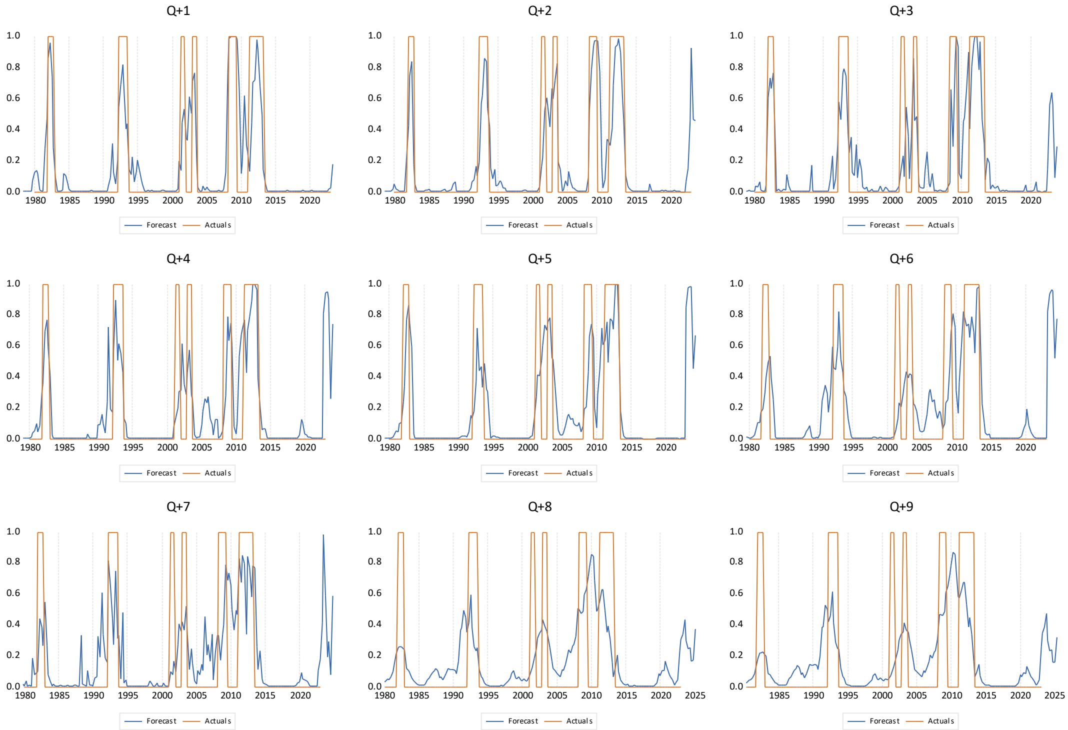
Germany



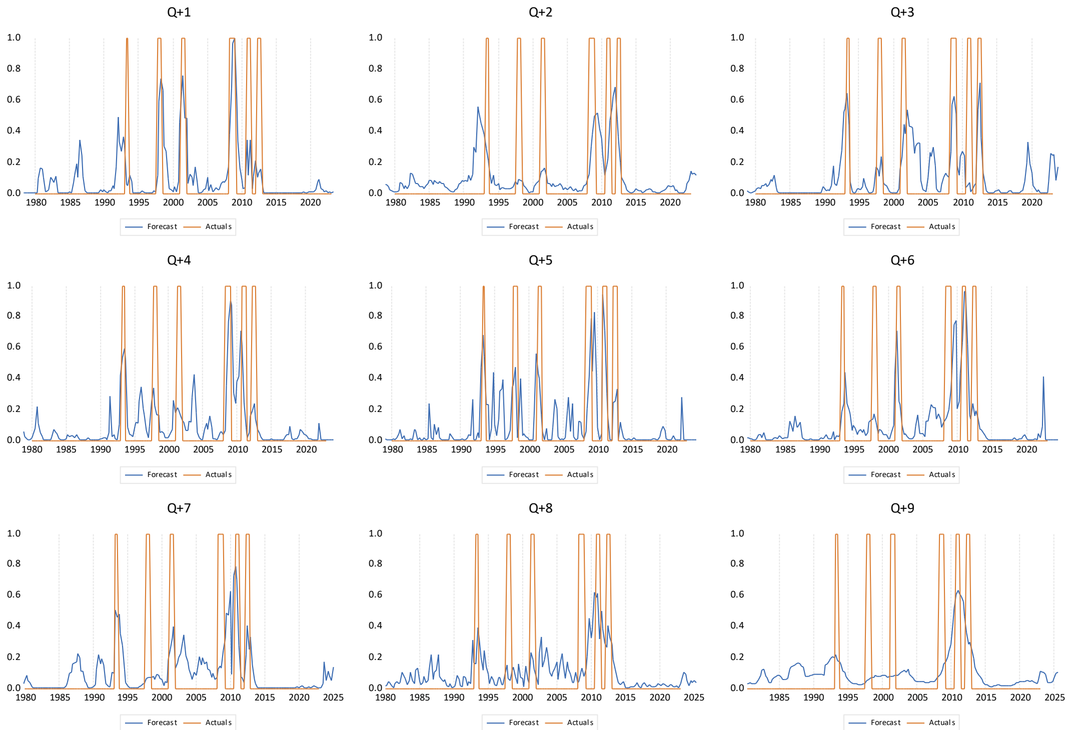
Greece



Italy


Q+1
Q+2
Q+3
Q+4
Q+5
Q+6
Q+7
Q+8
Q+9
Forecast
Actuals

Japan


Q+1
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Q+4
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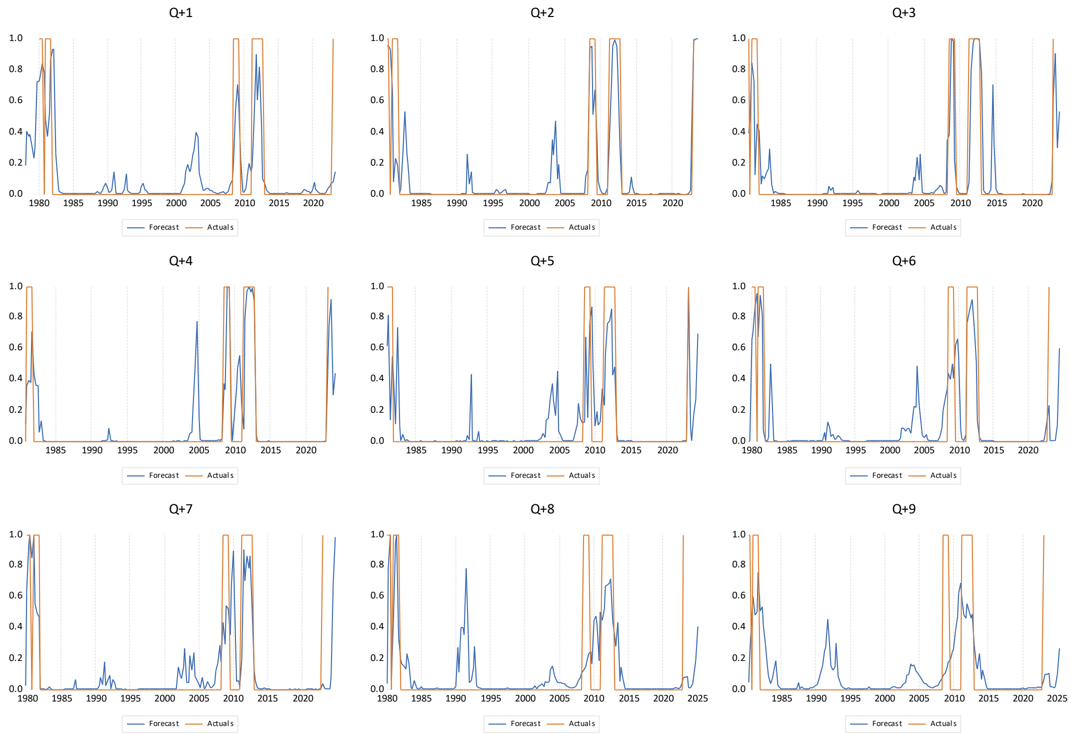
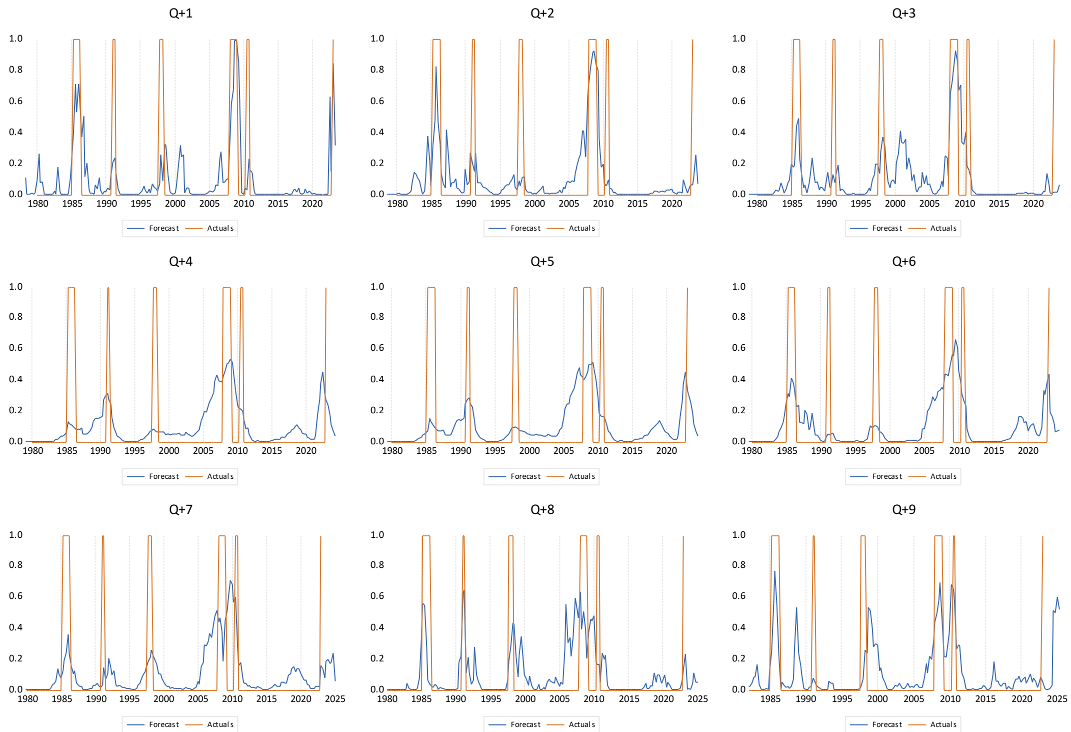
Q+6
Q+7
Q+8
Q+9
Forecast
Actuals

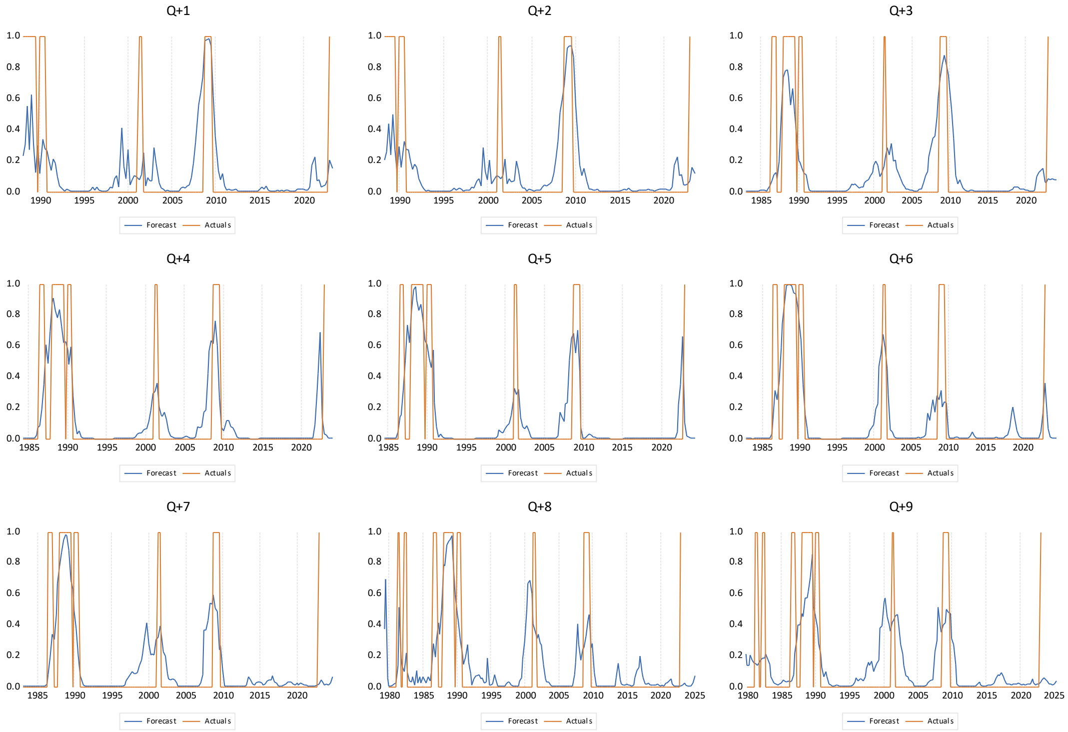
Netherlands



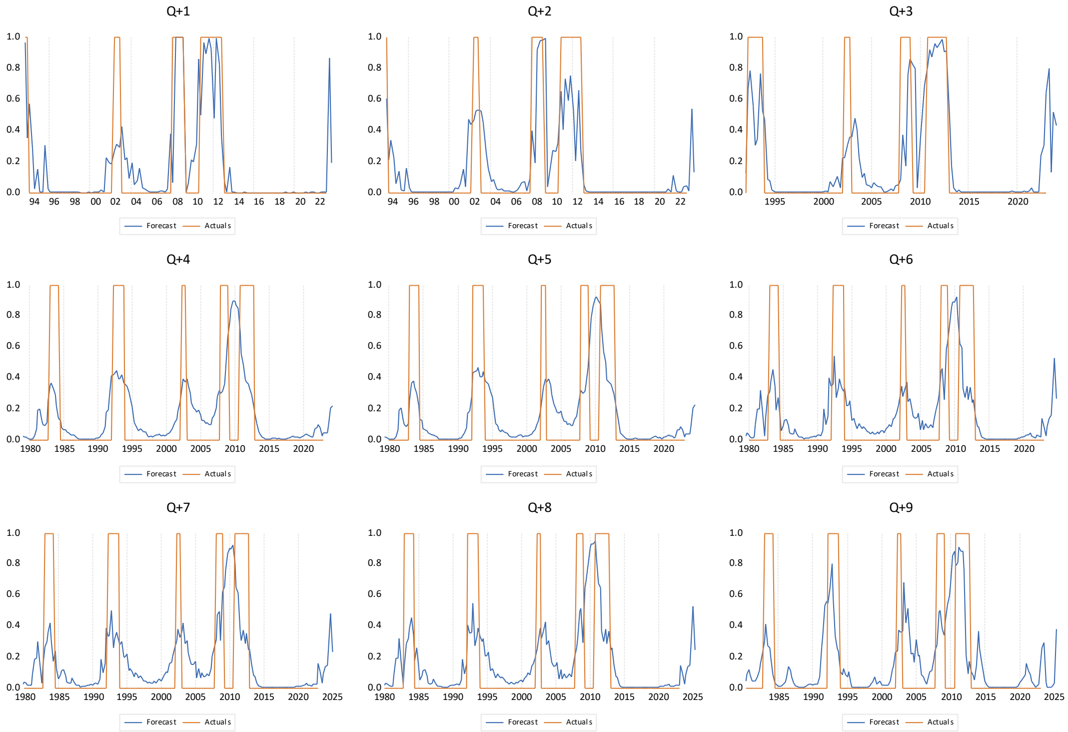
New Zealand



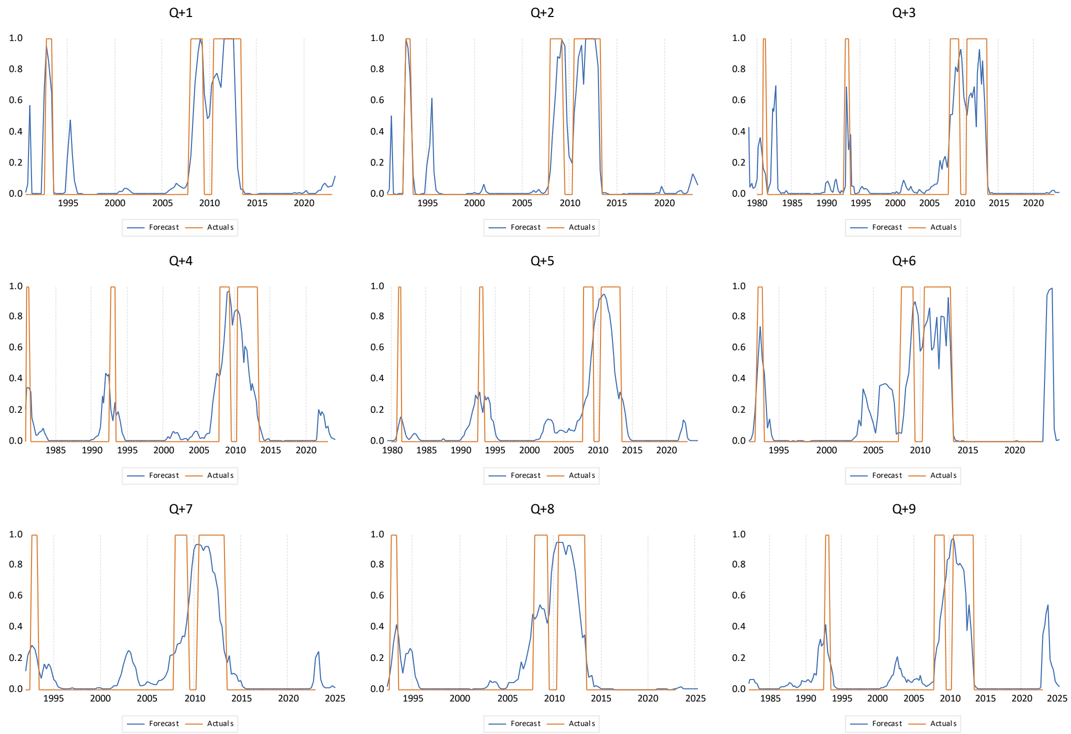
Norway



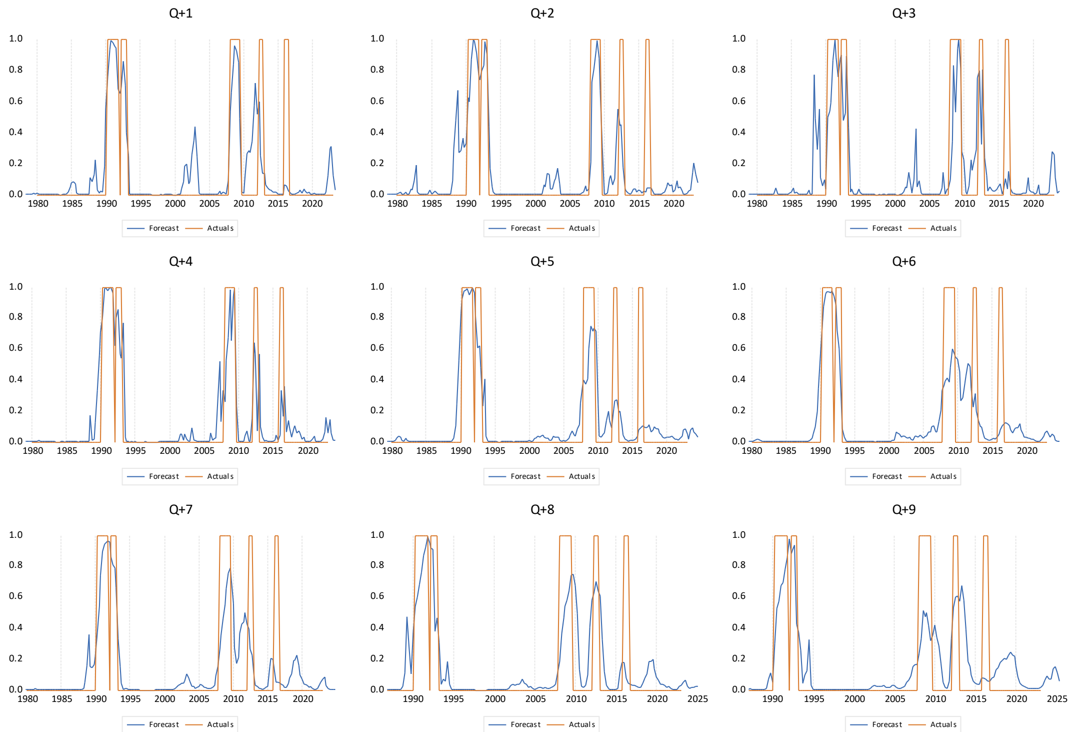
Portugal



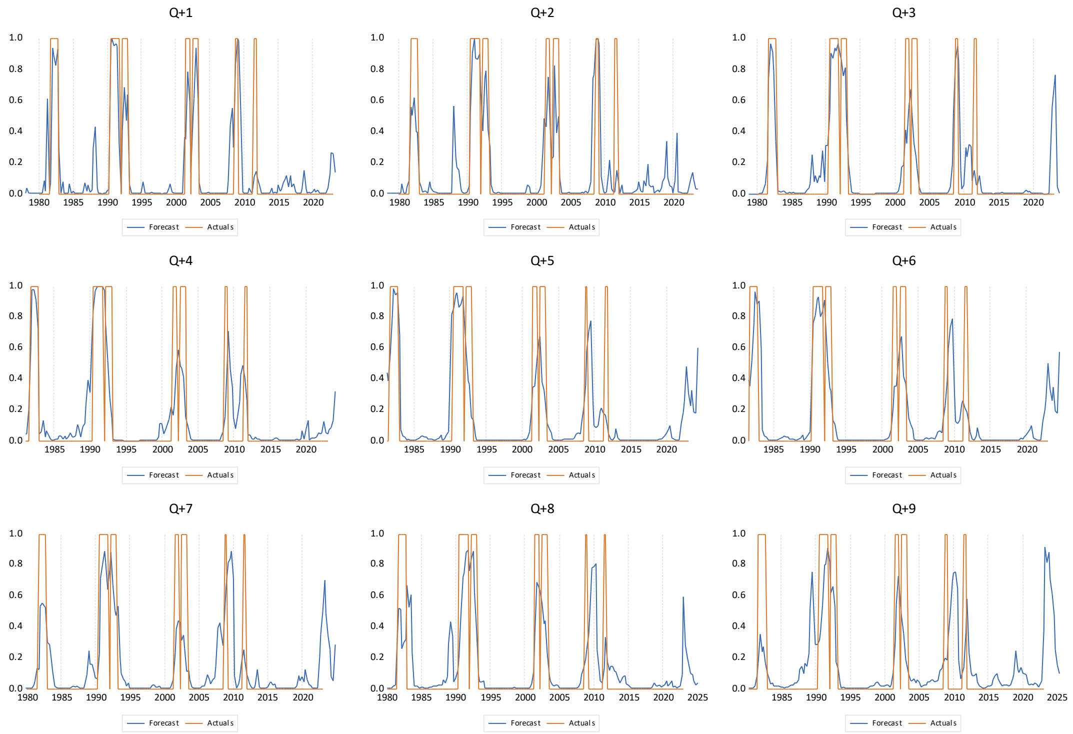
Spain



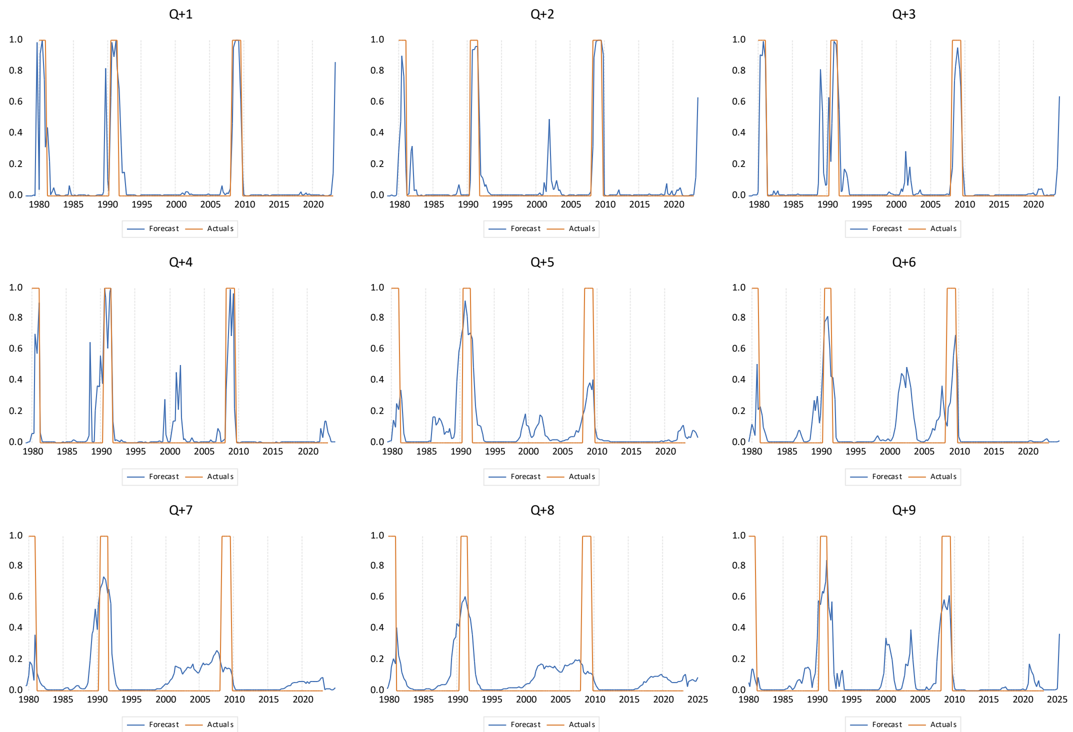
Sweden



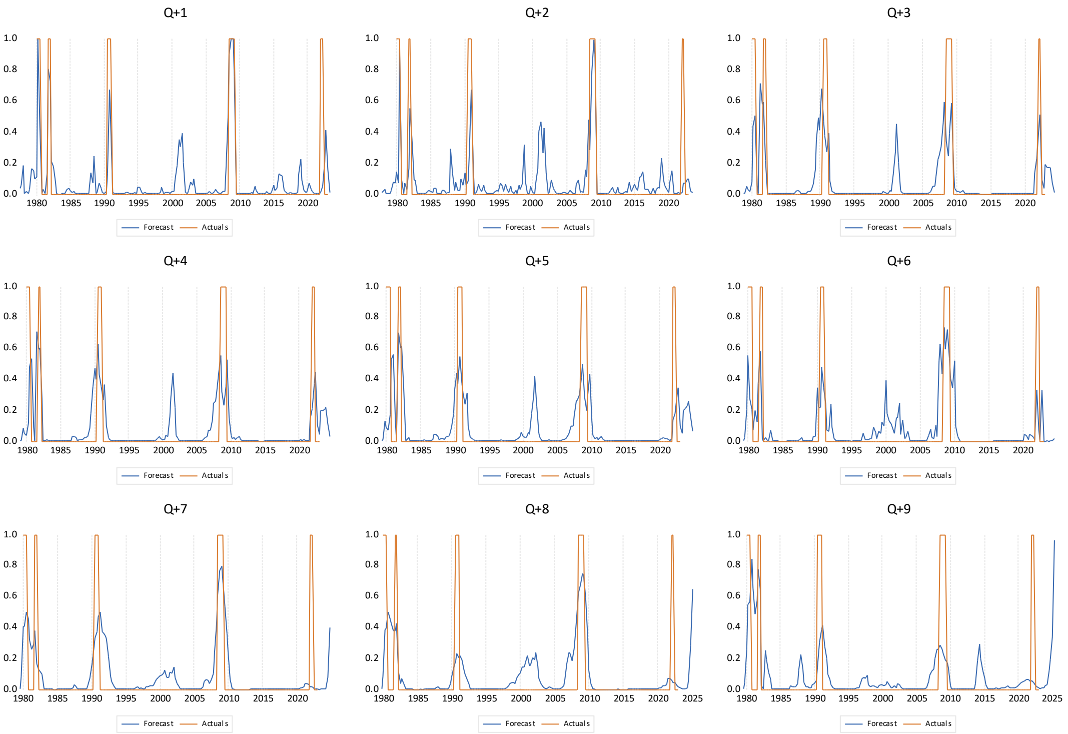
Switzerland



United Kingdom

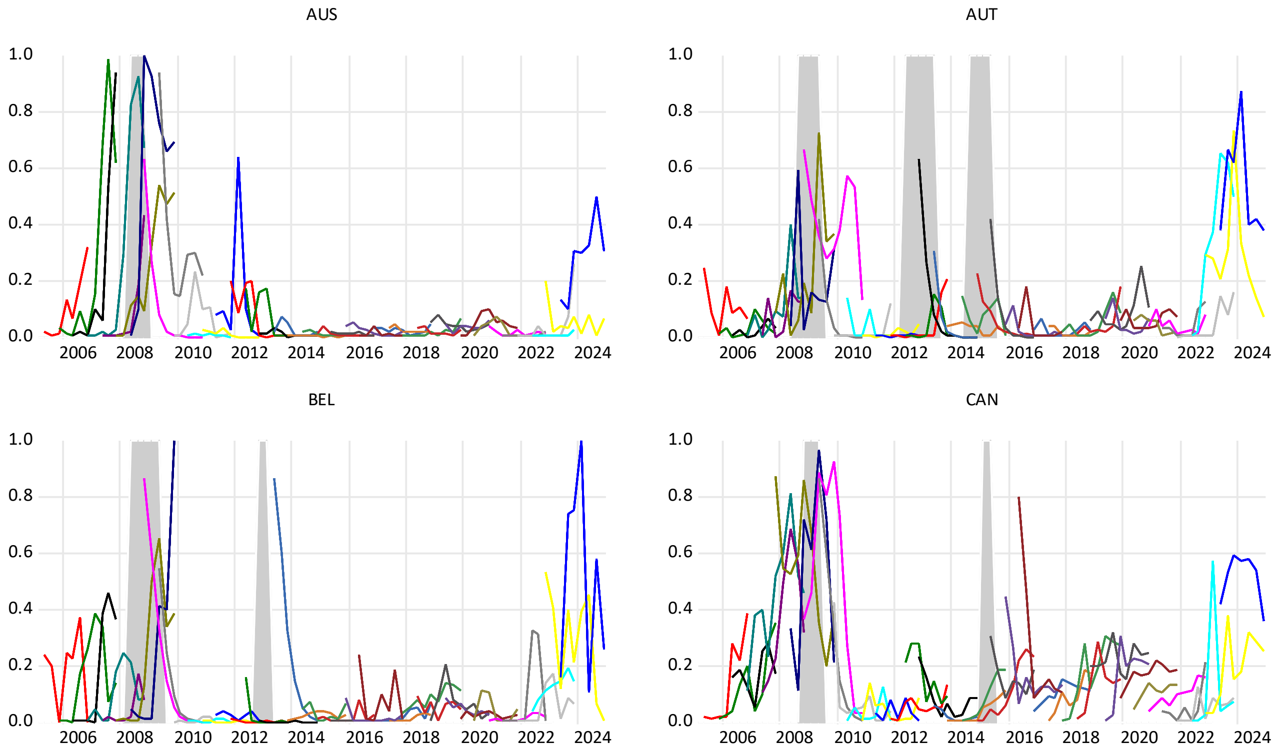


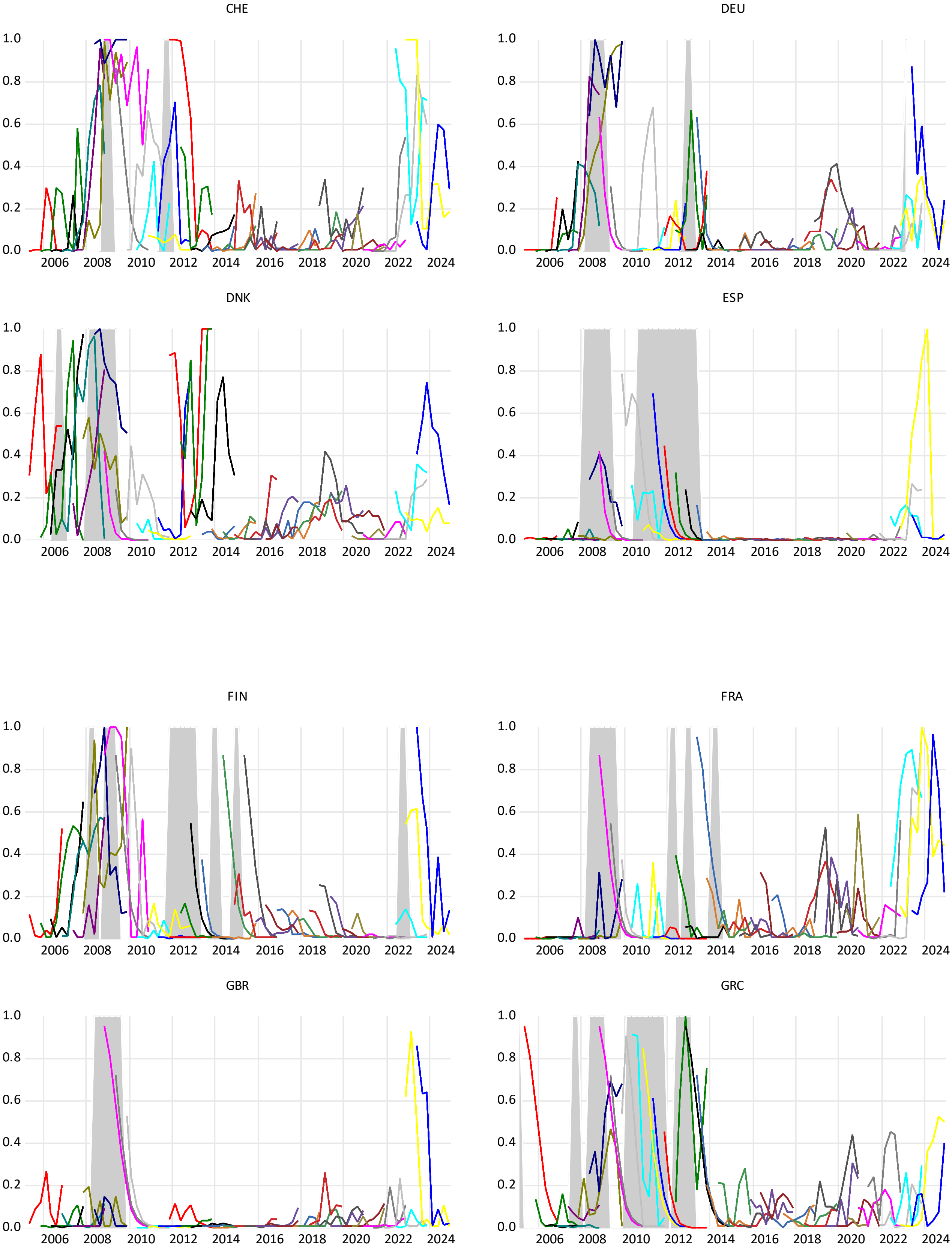
United States



Annex B. Recursive quarterly forecasts ("out-of-sample" forecasts)

The following sets of charts show the out-of-sample predictions of successive vintages of models selected by the algorithm every 2 quarters from 2005 Q2 to 2023 Q2. The timing of these updates is chosen to coincide roughly with successive publication dates of the Economic Outlook. The grey shaded areas correspond with realised downturn periods.




CHE
DEU
DNK
ESP
FIN
FRA
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0.4
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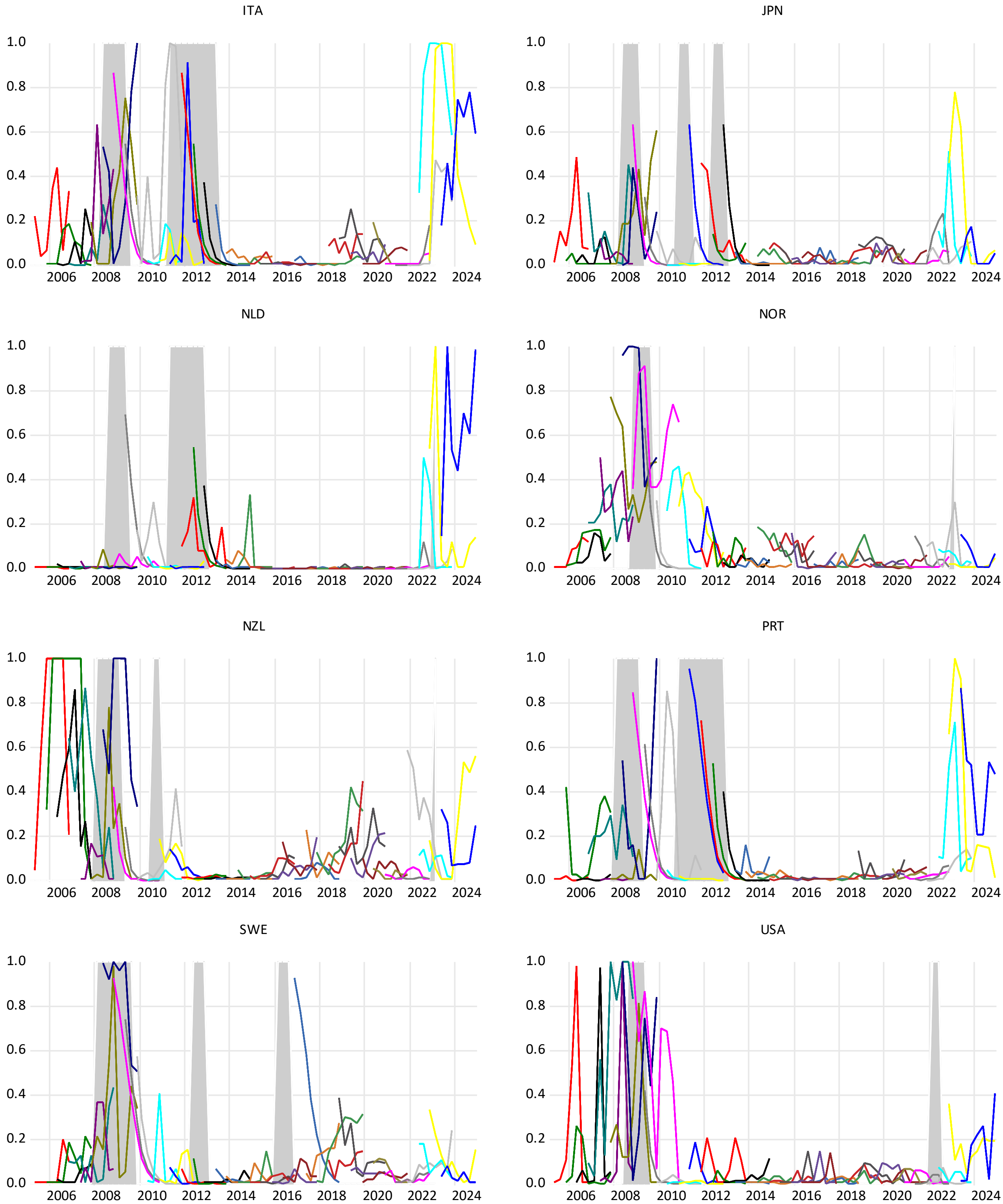
2006 2008 2010 2012 2014 2016 2018 2020 2022 2024


ITA
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USA
1.0
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2006
2008
2010
2012
2014
2016
2018
2020
2022
2024

Annex C. Country details of latest Doombot equations and predictions

This Annex provides a summary of the latest selected equations and predictions for each country in the form of a table and bar chart for each country.

Country-specific tables

The country-specific tables in this Annex report the coefficients of the equations used to obtain the downturn forecasts to end-2023 that are summarised in section 5 of the paper. The notation of the variables (as shown in the first column of these tables) follows the format CCC_VVV_FFF, where: CCC denotes the country ISO code or region (OECD or euro area [EAX]); VVV denotes the variable as summarised Table A.C.1, panel A; and FFF denotes the functional form that the variable takes as summarised Table A.C.1, panel B.

Each column summarises an equation at a different quarterly horizon, from 1 to 9 quarters. The final three columns of the table provide information on the average values of the explanatory variables in non-downturn periods, downturn periods as well as the latest value of that variable, respectively. If the latest value exceeds the average downturn value, in the sense of contributing to a larger downturn probability, then the cell is shaded red.

A summary statistic for the percentage of correct predictions ("% correct") is computed by first assigning predicted probabilities to be a downturn or non-downturn depending on whether they exceed 0.15, before comparing them with outcomes.

Country-specific bar charts

The stacked bar chart shows a decomposition of the factors contributing to downturn probabilities in each quarter. The bars provide a decomposition in terms of a linear total (on the left hand scale), represented by the black solid line, which are then converted to a probability between 0 and 1 by the cumulative normal distribution represented by the blue line (on the right hand scale). The different segments of each bar provide a decomposition of the linear total in terms of the explanatory variables in the equation.

Table A C.1. Variable and functional form notations

A. Variable notation

Domestic business cycle	
Capacity utilisation	CAPU
Industrial production	INDPRO
Unemployment rate	UNR
Domestic financial	
Slope of yield curve	YC
Short-term interest rates	IRS
Real share prices	RSP
Credit	
Total, share in GDP	LTNFQ
Bank, share in GDP	LBANFQ
House prices	
Real, relative to consumer prices	RHP
Price-to-rent ratio	HPI_RPI
Price-to-household income ratio	HPI_YDH
International	
Real oil price	WPOIL
OECD/Euro area/USA real share prices[1, 2]	CCC_RSP
OECD/Euro area/USA total credit share in GDP[1, 2]	CCC_LTNFQ
OECD/Euro area/USA bank credit share in GDP[1, 2]	CCC_LBANFQ
Euro area bond spread, upper quartile[1]	SPREAD
USA real house prices[2]	USA_RHP

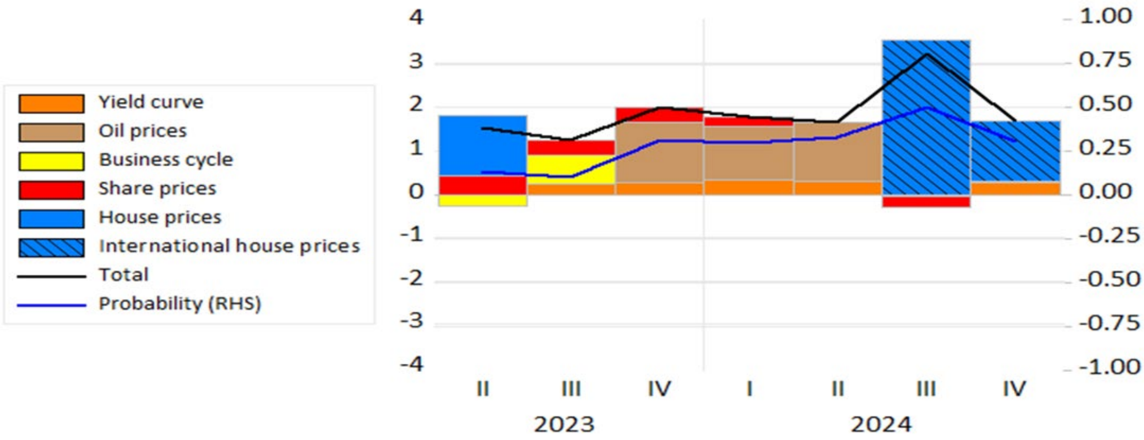
B. Functional forms

D0	Quarter-on-quarter change
D1	Year-on-year change
D3	3-year change
D5	5-year change
D1_3	1-year minus 3-year change
D1_5	1-year minus 3-year change
G0	Quarter-on-quarter growth rate
G1	Year-on-year growth rate
G3	3-year growth rate
G5	5-year growth rate
G1_3	1-year minus 3-year growth rate
G1_5	1-year minus 5-year growth rate

Note: (1) Euro area wide variables only appear in euro area countries. (2) Variables for the USA can appear in the equations for Canada.

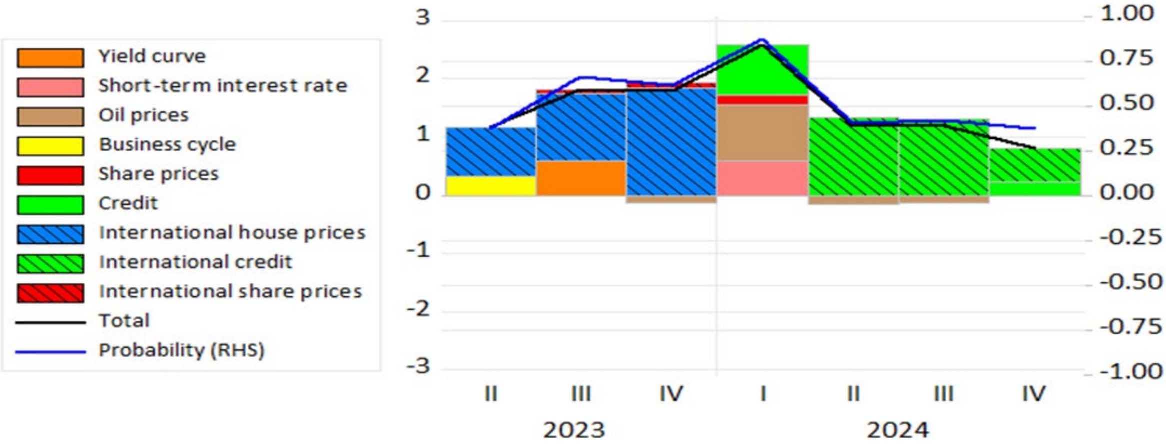
Australia

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
AUS_UNR_D1(-1)	0.65 ***									-0.1	0.9	-0.5
AUS_RHP_DG0_3(-2)	-0.08 ***									1.3	-10.0	-18.0
AUS_RSP_DG1_5	-0.06 ***									2.8	-20.4	-5.1
AUS_YC(-1)		-0.37 ***								0.4	-1.0	-0.4
AUS_UNR_D0_3(-2)		0.52 ***								-0.2	1.5	1.2
AUS_RSP_DG1_5(-1)		-0.05 ***								3.0	-21.8	-5.1
AUS_WPOIL_G3(-2)			0.04 ***							0.7	16.1	34.1
AUS_RSP_DG1_5(-2)			-0.05 ***							2.9	-18.3	-5.1
AUS_YC(-2)			-0.44 ***							0.5	-1.7	-0.4
AUS_WPOIL_G3(-3)				0.04 ***						0.6	15.8	34.1
AUS_RSP_DG1_5(-3)				-0.03 ***						2.7	-14.1	-5.1
AUS_YC(-3)				-0.52 ***						0.5	-1.9	-0.4
AUS_WPOIL_G3(-4)					0.04 ***					0.5	16.5	34.1
AUS_YC(-4)					-0.48 ***					0.4	-1.7	-0.4
OECD_RHP_DG1_3(-7)						-0.58 ***				0.2	-1.0	-4.4
AUS_GDPV_CAP_G3(-6)						1.29 ***				1.6	2.4	1.6
AUS_RSP_G5(-5)						0.13 ***				2.6	7.4	0.3
OECD_RHP_G5(-7)						0.36 ***				1.3	3.2	4.2
OECD_RHP_DG1_3(-8)							-0.31 ***			0.2	-0.7	-4.4
AUS_RSP_G3(-6)							0.07 ***			2.6	11.4	3.4
AUS_YC(-6)							-0.44 ***			0.4	-1.8	-0.4
OECD_RHP_DG1_3(-9)								-0.48 ***		0.1	-0.6	-4.4
AUS_GDPV_CAP_G5(-8)								1.34 **		1.6	2.2	1.0
AUS_RSP_G3(-7)								0.11 ***		2.5	12.5	3.4
AUS_YC(-7)								-0.43 ***		0.4	-1.5	-0.4
OECD_RHP_G3(-10)									0.57 ***	1.3	3.9	5.4
AUS_RSP_G3(-8)									0.10 ***	2.4	13.1	3.4
McFadden R2	0.59	0.53	0.54	0.49	0.36	0.43	0.4	0.47	0.43			
% of correct predictions	95.4	91.9	93.6	91.9	86.1	89.6	89.0	89.6	89.6			
No. of observations	173	173	173	173	173	173	173	173	173			



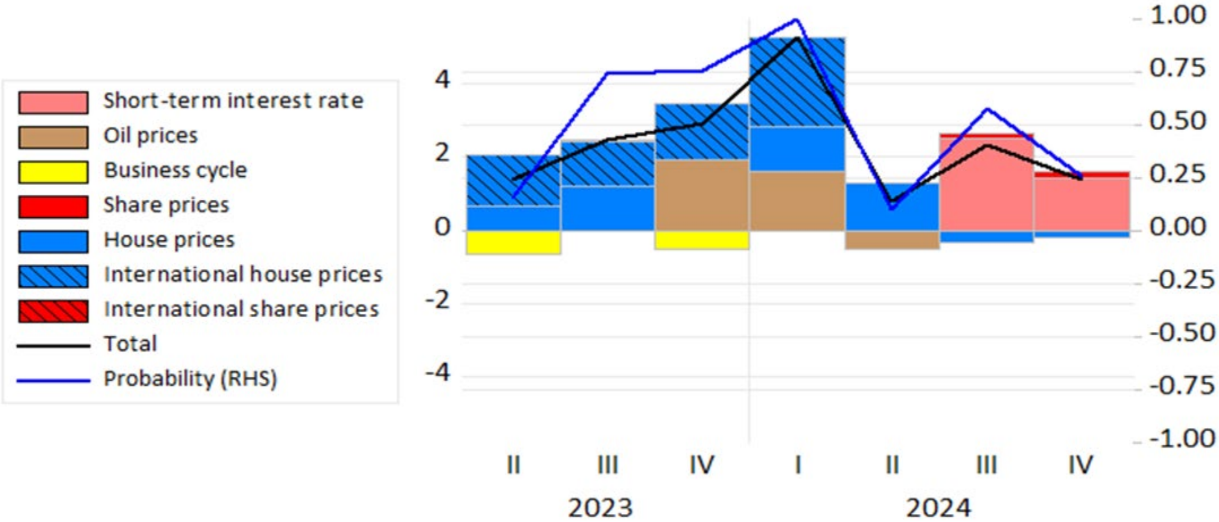
Austria

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
EAX_RHP_G1(-2)	-0.13 ***									1.8	-1.5	-5.0
AUT_GDPV_CAP_G0_3(-1)	-0.38 ***									0.6	-2.4	-0.7
AUT_YC(-1)		-0.41 ***								1.2	0.4	-0.4
EAX_RSP_G1(-1)		-0.02 ***								7.6	-6.4	2.1
EAX_RHP_G1(-3)		-0.18 ***								1.8	-1.2	-5.0
OECD_RSP_G0_3(-2)			-0.02 ***							4.5	-9.4	-2.9
EAX_RHP_G0(-4)			-0.51 ***							0.5	-0.5	-3.3
AUT_WPOIL_G5(-2)			0.06 ***							-0.2	10.4	-1.2
AUT_IRS_D0(-3)				0.77 ***						-0.1	0.3	0.8
AUT_LBANFQ_D1_5(-6)				-0.33 ***						0.2	-0.9	-2.7
AUT_RSP_G1_5(-3)				-0.02 ***						5.9	-9.2	-3.4
AUT_WPOIL_G3(-3)				0.03 ***						0.1	11.6	34.1
EAX_LBANFQ_D1_3(-7)					-0.41 ***					0.2	-0.6	-3.3
AUT_WPOIL_G5(-4)					0.06 ***					-0.4	11.1	-1.2
EAX_LBANFQ_D1_3(-8)						-0.40 ***				0.2	-0.5	-3.3
AUT_WPOIL_G5(-5)						0.05 ***				-0.2	9.9	-1.2
OECD_LTNFQ_D0(-9)							-0.39 **			0.5	0.1	-1.2
AUT_LBANFQ_D3(-9)							0.27 ***			0.8	1.8	1.9
OECD_LTNFQ_D0(-10)								-0.47 **		0.5	0.2	-1.2
AUT_INDPRO_G3(-8)								0.19 ***		2.9	3.8	4.5
OECD_LBANFQ_D5(-10)								0.42 **		0.4	0.8	0.3
EAX_SPREAD(-7)								0.30 **		-0.3	0.4	0.1
AUT_INDPRO_G3(-9)									0.17 ***	2.9	3.7	4.5
EAX_LTNFQ_D5(-11)									0.16 **	1.6	2.6	0.5
EAX_SPREAD(-8)									0.55 ***	-0.3	0.7	0.1
McFadden R2	0.34	0.28	0.3	0.29	0.25	0.2	0.11	0.16	0.2			
% of correct predictions	80.4	78.0	81.9	76.3	72.8	74.4	68.2	72.3	68.6			
No. of observations	173	173	171	173	169	168	173	173	172			



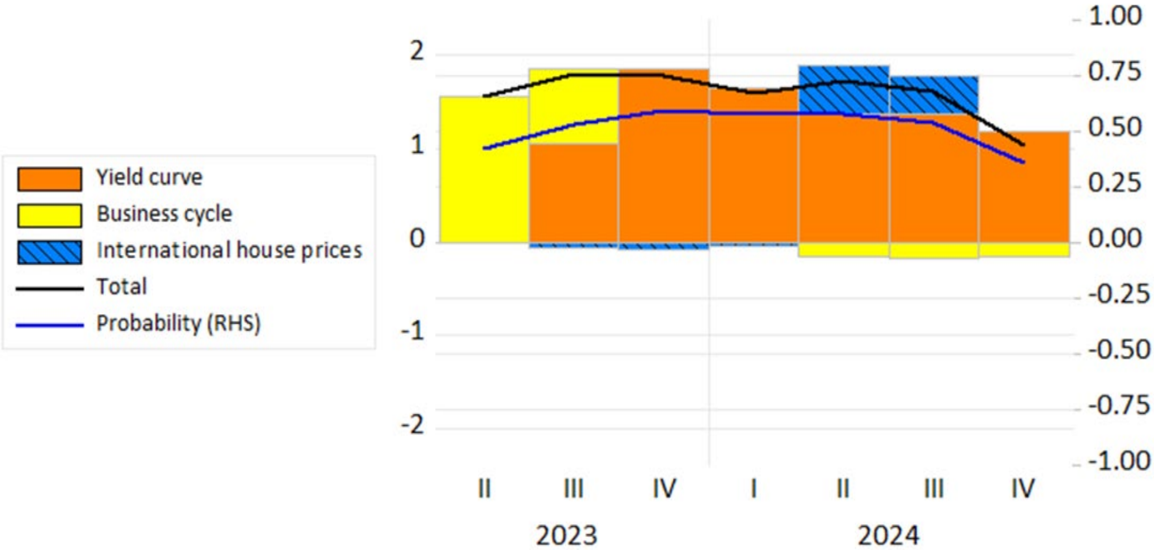
Belgium

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
BEL_HPI_RPI_G1_3(-2)	-0.31 ***									0.4	-2.9	-2.1
EAX_RHP_G1_3(-2)	-0.21 ***									0.3	-2.4	-6.9
BEL_CAPU_D0	-1.17 ***									0.2	-1.4	0.6
OECD_RSP_G1_5(-1)		-0.04 ***								2.6	-12.0	-0.1
EAX_RHP_G1_5(-3)		-0.17 ***								0.4	-2.9	-7.4
BEL_HPI_YDH_G1_3(-3)		-0.22 ***								0.3	-3.2	-5.5
OECD_RHP_G0(-4)			-0.97 ***							0.5	-0.3	-1.1
BEL_WPOIL_G3(-2)			0.06 ***							0.0	16.6	34.1
BEL_GDPV_CAP_G5(-3)			0.82 ***							1.4	2.3	0.9
BEL_HPI_RPI_G3(-5)				0.23 ***						0.9	4.9	2.1
BEL_RHP_G1_3(-5)				-0.22 ***						0.3	-3.0	-5.2
BEL_WPOIL_G3(-3)				0.05 ***						-0.2	17.8	34.1
EAX_RHP_G0_3(-5)				-0.17 ***						0.5	-3.8	-14.5
BEL_HPI_YDH_G1_3(-6)					-0.21 ***					0.2	-2.2	-5.5
BEL_HPI_RPI_G3(-6)					0.24 ***					0.8	5.1	2.1
BEL_WPOIL_G1(-4)					0.01 ***					2.8	37.0	-31.8
BEL_RSP_G1_5(-5)						-0.03 ***				2.5	-13.0	-4.5
BEL_RHP_G5(-7)						0.32 ***				1.7	5.5	1.1
BEL_IRS_D1_5(-5)						0.84 ***				-0.2	1.5	3.0
BEL_RSP_G1_5(-6)							-0.03 ***			2.1	-11.7	-4.5
BEL_IRS_D0(-6)							1.87 ***			-0.1	0.5	0.8
BEL_HPI_YDH_G3(-8)							0.31 ***			0.5	4.6	0.3
BEL_RSP_G1_3(-7)								-0.03 ***		1.9	-11.6	-12.3
BEL_HPI_YDH_G5(-9)								0.27 ***		0.6	3.8	0.5
OECD_LBANFQ_D5(-11)									0.92 ***	0.4	0.9	0.3
BEL_RSP_G5(-8)									0.09 ***	2.1	9.3	-5.6
McFadden R2	0.53	0.41	0.46	0.53	0.39	0.39	0.42	0.22	0.32			
% of correct predictions	89.6	84.4	87.3	86.0	84.7	86.6	88.1	84.2	79.0			
No. of observations	173	173	173	171	170	127	126	133	124			



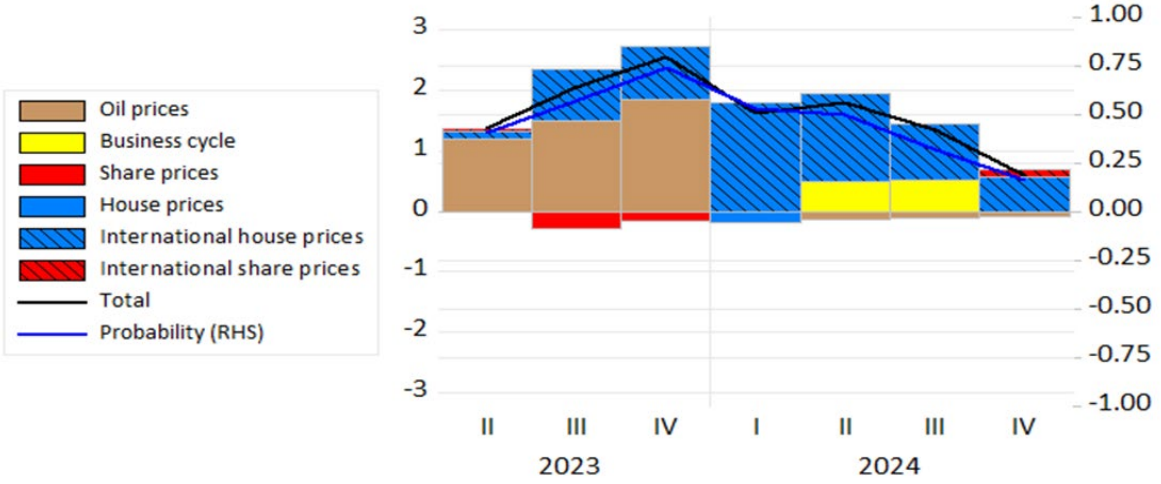
Canada

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
CAN_GDPV_CAP_G1(-1)	-0.48 ***									1.5	-0.5	0.7
CAN_CAPU_D0_5	-0.26 ***									1.0	-5.6	-5.1
CAN_INDPRO_G1_5(-2)		-0.15 ***								0.5	-2.9	1.3
CAN_USA_RHP_G1(-3)		-0.11 ***								2.4	-1.4	2.6
CAN_CAPU_D0_3(-1)		-0.11 ***								0.7	-3.9	-8.9
CAN_YC(-1)		-0.43 ***								1.1	-0.9	-1.8
CAN_USA_RHP_G1(-4)			-0.14 ***							2.3	-1.0	2.6
CAN_YC(-2)			-0.77 ***							1.1	-1.2	-1.8
CAN_USA_RHP_G1(-5)				-0.10 ***						2.2	-0.3	2.6
CAN_YC(-3)				-0.68 ***						1.1	-1.2	-1.8
CAN_CAPU_D5(-4)					0.44 ***					-0.1	0.6	-0.4
CAN_USA_RHP_G0(-6)					-0.45 ***					0.6	-0.2	-0.7
CAN_YC(-4)					-0.56 ***					1.1	-1.0	-1.8
CAN_USA_RHP_G0(-7)						-0.37 ***				0.5	-0.1	-0.7
CAN_CAPU_D5(-5)						0.48 ***				-0.1	0.7	-0.4
CAN_YC(-5)						-0.56 ***				1.1	-1.1	-1.8
CAN_CAPU_D5(-6)							0.43 ***			-0.2	0.9	-0.4
CAN_YC(-6)							-0.49 ***			1.0	-0.9	-1.8
CAN_CAPU_D5(-7)								0.46 ***		-0.2	1.0	-0.4
CAN_YC(-7)								-0.43 ***		1.0	-0.7	-1.8
CAN_YC(-8)									-0.35 ***	0.9	-0.5	-1.8
CAN_CAPU_D5(-8)									0.48 ***	-0.2	1.0	-0.4
McFadden R2	0.52	0.49	0.47	0.4	0.41	0.41	0.32	0.3	0.26			
% of correct predictions	86.1	87.9	85.6	82.7	86.7	82.7	78.6	76.9	73.4			
No. of observations	173	173	173	173	173	173	173	173	173			



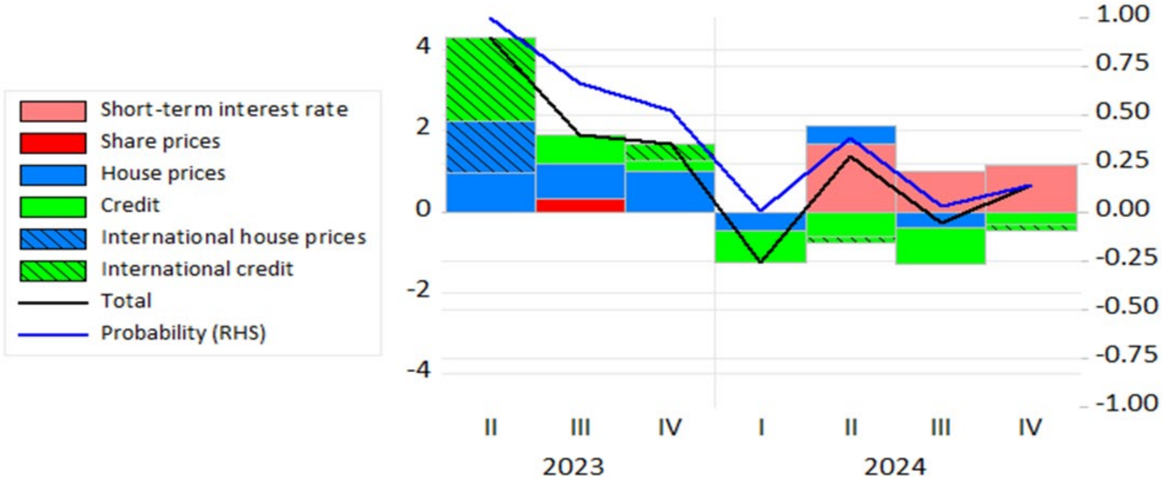
Denmark

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
OECD_RHP_G1(-2)	-0.16 ***									2.0	-0.4	1.0
DNK_WPOIL_G3	0.04 ***									0.3	12.3	34.1
OECD_RSP_G1_5	-0.03 ***									2.6	-10.6	-0.1
DNK_WPOIL_G3(-1)		0.05 ***								0.0	14.7	34.1
OECD_RHP_G1_5(-3)		-0.25 ***								0.5	-2.1	-3.2
DNK_RSP_G0(-1)		-0.08 ***								3.1	-6.2	6.0
OECD_RHP_G1_5(-4)			-0.25 ***							0.4	-1.4	-3.2
DNK_RSP_G0_3(-2)			-0.02 ***							6.7	-20.4	13.6
DNK_WPOIL_G3(-2)			0.06 ***							-0.2	16.7	34.1
DNK_HPI_YDH_G3(-5)				0.09 ***						1.3	5.2	-0.3
OECD_RHP_G1_3(-5)				-0.40 ***						0.3	-1.0	-4.4
DNK_GDPV_CAP_G3(-5)					0.65 ***					1.4	2.1	2.3
OECD_RHP_G1_3(-6)					-0.32 ***					0.2	-0.8	-4.4
DNK_WPOIL_G5(-4)					0.06 ***					0.0	10.9	-1.2
DNK_GDPV_CAP_G3(-6)						0.69 ***				1.4	2.1	2.3
OECD_RHP_G5(-7)						0.35 ***				1.3	2.7	4.2
DNK_WPOIL_G5(-5)						0.04 ***				0.0	10.5	-1.2
OECD_RSP_G3(-6)							0.06 ***			4.3	7.9	6.5
OECD_RHP_G5(-8)							0.22 ***			1.2	2.7	4.2
DNK_WPOIL_G5(-6)							0.04 ***			0.1	9.7	-1.2
DNK_WPOIL_G1(-7)								0.01 ***		3.0	22.7	-31.8
DNK_RSP_G3(-7)								0.07 ***		5.8	15.7	12.5
DNK_WPOIL_G1(-8)									0.02 ***	1.9	24.3	-31.8
DNK_RSP_G3(-8)									0.08 ***	5.7	15.9	12.5
McFadden R2	0.29	0.43	0.41	0.27	0.32	0.31	0.28	0.24	0.29			
% of correct predictions	80.4	85.5	83.0	86.8	84.6	88.1	86.2	79.6	79.4			
No. of observations	173	159	147	152	169	168	167	142	141			



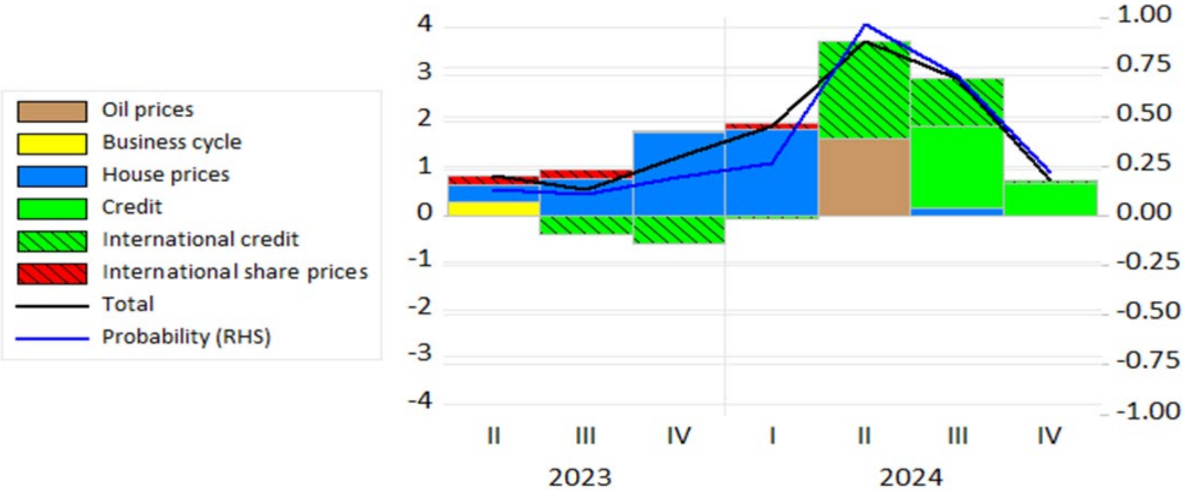
Finland

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
EAX_LBANFQ_D1_3(-3)	-0.64 ***									0.2	-1.1	-3.3
FIN_HPI_RPI_G0_5(-2)	-0.08 ***									2.2	-7.5	-12.1
OECD_RHP_G1_3(-2)	-0.28 ***									0.4	-1.5	-4.4
FIN_RSP_G0(-1)		-0.04 ***								3.8	-6.3	-6.1
FIN_LBANFQ_D1_5(-4)		-0.36 ***								0.4	-1.7	-2.0
FIN_HPI_RPI_G0_5(-3)		-0.07 ***								2.2	-7.4	-12.1
EAX_LBANFQ_D0_3(-5)			-0.23 ***							0.4	-1.9	-1.9
FIN_LBANFQ_D1_5(-5)			-0.27 ***							0.4	-1.4	-2.0
FIN_LBANFQ_D5(-5)			0.34 ***							1.1	2.8	0.4
FIN_RHP_G0_3(-4)			-0.07 ***							2.0	-7.4	-14.9
FIN_LBANFQ_D0_3(-6)				-0.21 ***						0.4	-1.8	-1.3
FIN_LTNFQ_D5(-6)				0.32 ***						1.9	4.7	-1.0
FIN_HPI_YDH_G5(-5)				0.33 ***						-0.6	2.0	-1.7
FIN_IRS_D1_5(-4)					0.56 ***					-0.1	1.0	3.0
FIN_HPI_RPI_G1_3(-6)					-0.11 ***					1.0	-3.0	-4.2
FIN_LTNFQ_D5(-7)					0.19 ***					1.9	4.6	-1.0
OECD_LBANFQ_D5(-7)					0.72 ***					0.3	1.2	0.3
FIN_IRS_D1_5(-5)						0.33 ***				-0.2	1.0	3.0
FIN_LTNFQ_D5(-8)						0.27 ***				2.0	4.5	-1.0
FIN_HPI_YDH_G5(-7)						0.26 ***				-0.7	2.2	-1.7
FIN_IRS_D1_5(-6)							0.39 ***			-0.2	1.0	3.0
FIN_LBANFQ_D5(-9)							0.35 ***			1.0	3.3	0.4
OECD_LBANFQ_D5(-9)							0.84 ***			0.3	1.3	0.3
FIN_HPI_YDH_G3(-9)								0.15 ***		-1.1	3.3	-0.9
FIN_LBANFQ_D5(-10)								0.45 ***		1.0	3.3	0.4
FIN_HPI_YDH_G3(-10)									0.12 ***	-1.0	3.0	-0.9
FIN_LBANFQ_D5(-11)									0.41 ***	1.0	3.3	0.4
McFadden R2	0.44	0.39	0.45	0.42	0.46	0.4	0.44	0.38	0.33			
% of correct predictions	84.4	80.9	81.4	75.6	81.5	82.5	78.0	80.2	78.3			
No. of observations	173	173	172	168	173	166	168	167	166			



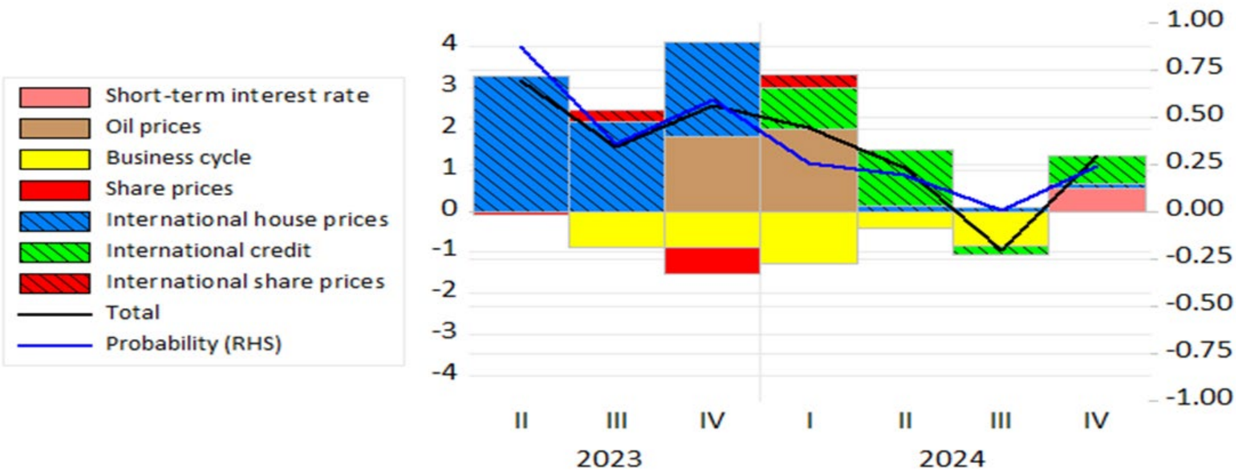
France

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
OECD_RSP_G1	-0.04 ***									7.8	-11.0	0.2
FRA_HPI_RPI_G1_3(-2)	-0.20 ***									0.6	-3.2	-1.7
FRA_GDPV_CAP_G0(-1)	-1.68 ***									0.4	-0.3	0.2
EAX_LTNFQ_D5(-4)		0.34 ***								1.5	3.3	0.5
FRA_HPI_RPI_G0_3(-3)		-0.11 ***								0.8	-4.2	-6.8
OECD_RSP_G1(-1)		-0.04 ***								8.0	-12.0	0.2
EAX_LTNFQ_D5(-5)			0.49 ***							1.5	3.3	0.5
FRA_RHP_G0_3(-4)			-0.18 ***							0.7	-4.0	-9.9
OECD_RSP_G0(-2)			-0.11 ***							2.1	-4.9	0.9
OECD_LBANFQ_D1_5(-6)				-0.45 ***						0.2	-1.0	-1.3
FRA_RHP_G0_3(-5)				-0.19 ***						0.6	-3.7	-9.9
EAX_LTNFQ_D5(-6)				0.53 ***						1.5	3.4	0.5
EAX_RSP_G0(-3)				-0.08 ***						2.1	-6.3	-0.3
EAX_LBANFQ_D1_3(-7)					-0.69 ***					0.2	-0.9	-3.3
FRA_WPOIL_G3(-4)					0.05 ***					0.1	14.1	34.1
OECD_LBANFQ_D5(-7)					0.75 ***					0.4	1.2	0.3
OECD_LBANFQ_D1_5(-8)						-0.79 ***				0.2	-0.7	-1.3
FRA_RHP_G3(-7)						0.26 ***				1.6	4.9	2.7
FRA_LBANFQ_D3(-8)						0.62 ***				0.7	2.1	3.8
FRA_LBANFQ_D5(-9)							0.28 ***			0.6	1.9	3.3
EAX_LBANFQ_D3(-9)							0.37 ***			0.5	2.1	0.8
FRA_WPOIL_G3(-7)								0.04 ***		0.0	13.8	34.1
OECD_LBANFQ_D5(-10)								1.04 ***		0.4	1.3	0.3
FRA_WPOIL_G3(-8)									0.05 ***	-0.1	14.9	34.1
OECD_LBANFQ_D5(-11)									1.16 ***	0.3	1.4	0.3
McFadden R2	0.46	0.41	0.46	0.5	0.4	0.37	0.24	0.33	0.38			
% of correct predictions	86.7	85.6	84.4	87.3	82.1	78.6	81.5	83.2	83.1			
No. of observations	173	173	173	173	173	173	173	173	172			



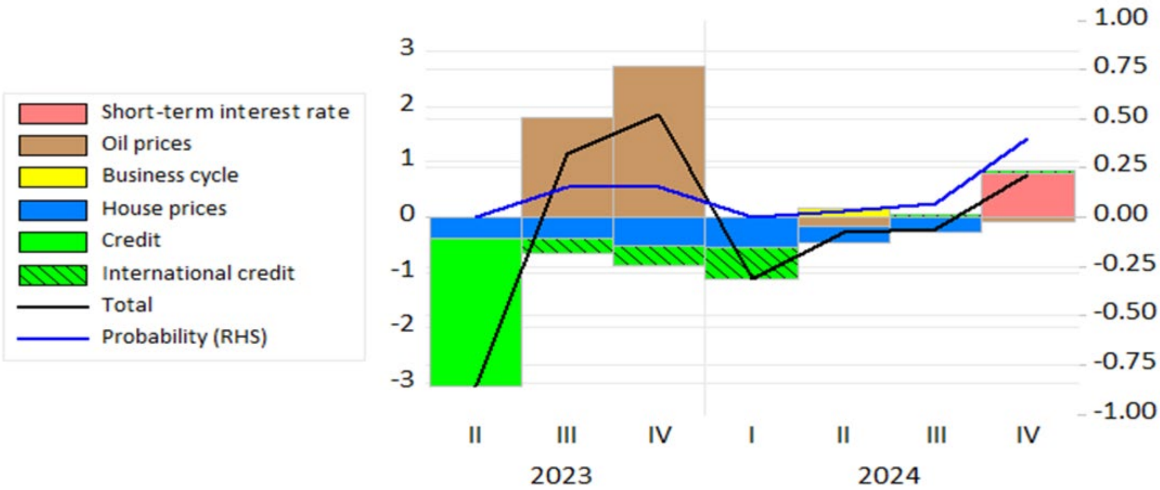
Germany

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
DEU_RSP_G1	-0.05 ***									9.1	-16.6	7.1
EAX_RHP_G1_3(-2)	-0.48 ***									0.5	-2.9	-6.9
DEU_GDPV_CAP_G3(-2)		0.58 ***								1.3	2.8	0.1
OECD_RSP_G1(-1)		-0.05 ***								8.6	-11.5	0.2
EAX_RHP_G0_3(-3)		-0.15 ***								0.7	-4.2	-14.5
DEU_RSP_G0(-2)			-0.09 ***							2.3	-6.1	8.3
DEU_WPOIL_G3(-2)			0.06 ***							-0.5	15.7	34.1
EAX_RHP_G0_3(-4)			-0.16 ***							0.7	-3.8	-14.5
DEU_GDPV_CAP_G3(-3)			0.57 ***							1.3	2.9	0.1
OECD_LBANFQ_D1_3(-6)				-0.65 ***						0.2	-0.7	-1.6
EAX_RSP_G0_3(-3)				-0.03 ***						8.0	-19.3	-8.1
DEU_WPOIL_G3(-3)				0.06 ***						-0.7	16.3	34.1
DEU_GDPV_CAP_G3(-4)				0.84 ***						1.4	2.9	0.1
OECD_LBANFQ_D1_3(-7)					-0.88 ***					0.2	-0.6	-1.6
DEU_INDPRO_G3(-5)					0.31 ***					1.0	3.4	-0.1
EAX_RHP_G3(-6)					0.25 ***					0.9	4.2	1.9
EAX_LTNFQ_D3(-8)						0.25 ***				1.6	2.9	0.9
DEU_GDPV_CAP_G5(-6)						0.51 ***				1.6	2.3	0.0
EAX_RHP_G3(-7)						0.19 ***				0.8	4.2	1.9
OECD_LBANFQ_D0_3(-9)							-0.33 ***			0.3	-0.9	-1.9
DEU_IRS_D0_5(-6)							0.25 ***			-0.2	1.4	2.3
EAX_LBANFQ_D3(-9)							0.53 ***			0.5	1.9	0.8
EAX_RHP_G3(-8)							0.24 ***			0.9	4.0	1.9
DEU_UNR_D3(-8)								-0.75 ***		0.1	-0.3	-0.2
EAX_RHP_G5(-9)								0.25 ***		1.0	3.2	2.4
DEU_WPOIL_G1(-7)								0.01 ***		1.1	30.4	-31.8
EAX_SPREAD(-8)									0.35 ***	-0.2	0.4	0.1
DEU_INDPRO_G3(-9)									0.17 ***	1.2	3.0	-0.1
OECD_LBANFQ_D3(-11)									0.47 ***	0.4	1.2	0.6
McFadden R2	0.55	0.54	0.58	0.58	0.42	0.29	0.41	0.26	0.22			
% of correct predictions	89.6	90.8	89.6	86.7	81.5	74.0	78.6	74.6	80.8			
No. of observations	173	173	173	173	173	173	173	173	172			



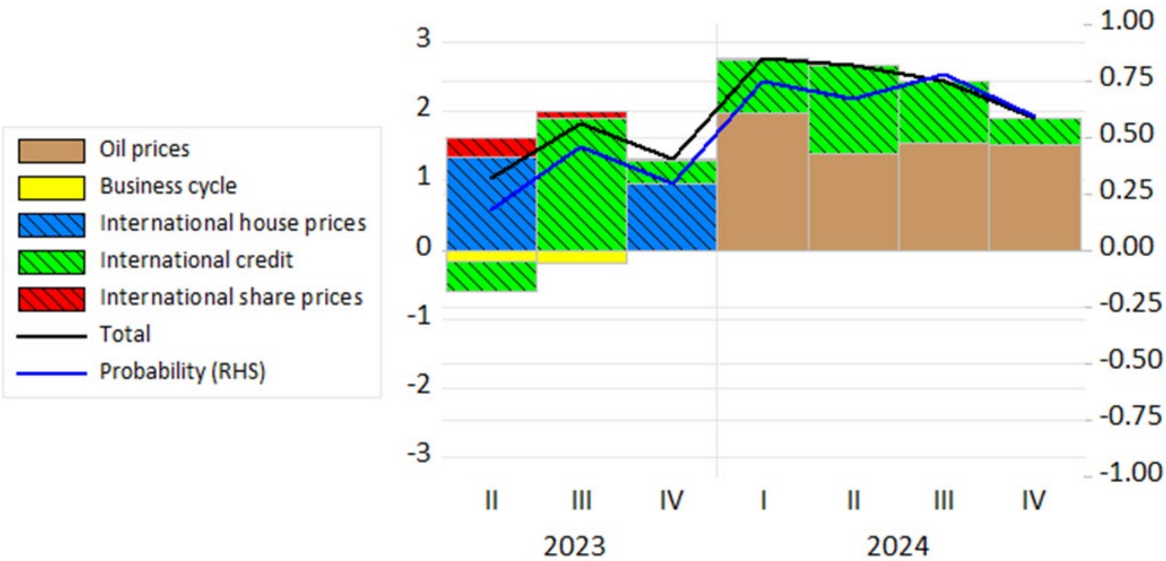
Greece

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
GRC_LBANFQ_D3(-3)	0.25 ***									0.0	3.0	-9.9
GRC_HPI_RPI_G0(-2)	-0.40 ***									1.0	-1.4	1.5
GRC_WPOIL_G3(-1)		0.06 ***								-0.9	9.6	34.1
OECD_LBANFQ_D5(-4)		1.27 ***								0.3	1.0	0.3
GRC_HPI_RPI_G0(-3)		-0.40 ***								0.9	-1.3	1.5
GRC_WPOIL_G3(-2)			0.08 ***							-1.0	10.1	34.1
OECD_LBANFQ_D5(-5)			1.70 ***							0.3	1.0	0.3
GRC_HPI_RPI_G0(-4)			-0.54 ***							0.9	-1.3	1.5
GRC_RHP_G0(-5)				-0.30 ***						0.8	-0.9	2.4
EAX_LBANFQ_D5(-6)				1.08 ***						0.4	1.5	0.2
GRC_WPOIL_G5(-4)					0.07 ***					-0.8	7.3	-1.2
GRC_HPI_RPI_G0(-6)					-0.28 ***					0.7	-0.7	1.5
GRC_GDPV_CAP_G0_5(-5)					-0.12 ***					1.0	-2.6	-1.2
GRC_HPI_RPI_G0(-7)						-0.29 ***				0.7	-0.6	1.5
OECD_LBANFQ_D3(-8)						0.82 ***				0.3	1.2	0.6
GRC_WPOIL_G5(-6)							0.03 ***			-0.9	7.3	-1.2
GRC_IRS_D1(-6)							0.20 ***			-0.7	1.0	3.7
OECD_LBANFQ_D3(-9)							0.70 ***			0.2	1.2	0.6
EAX_RSP_G1(-7)								-0.02 ***		8.4	-2.5	2.1
GRC_LBANFQ_D3(-10)								0.12 ***		0.3	3.7	-9.9
GRC_IRS_D1(-7)								0.52 ***		-0.9	1.3	3.7
OECD_LBANFQ_D3(-10)								0.58 ***		0.2	1.3	0.6
GRC_GDPV_CAP_G1_3(-9)									-0.18 ***	0.2	-1.3	0.1
GRC_LBANFQ_D3(-11)									0.14 ***	0.4	3.7	-9.9
OECD_LTNFQ_D3(-11)									0.36 ***	1.0	2.4	1.1
GRC_IRS_D1(-8)									0.63 ***	-0.9	1.4	3.7
McFadden R2	0.5	0.56	0.67	0.49	0.44	0.37	0.33	0.49	0.52			
% of correct predictions	85.3	89.1	91.0	82.8	81.6	80.4	71.9	83.2	79.7			
No. of observations	102	101	100	99	98	97	167	173	172			



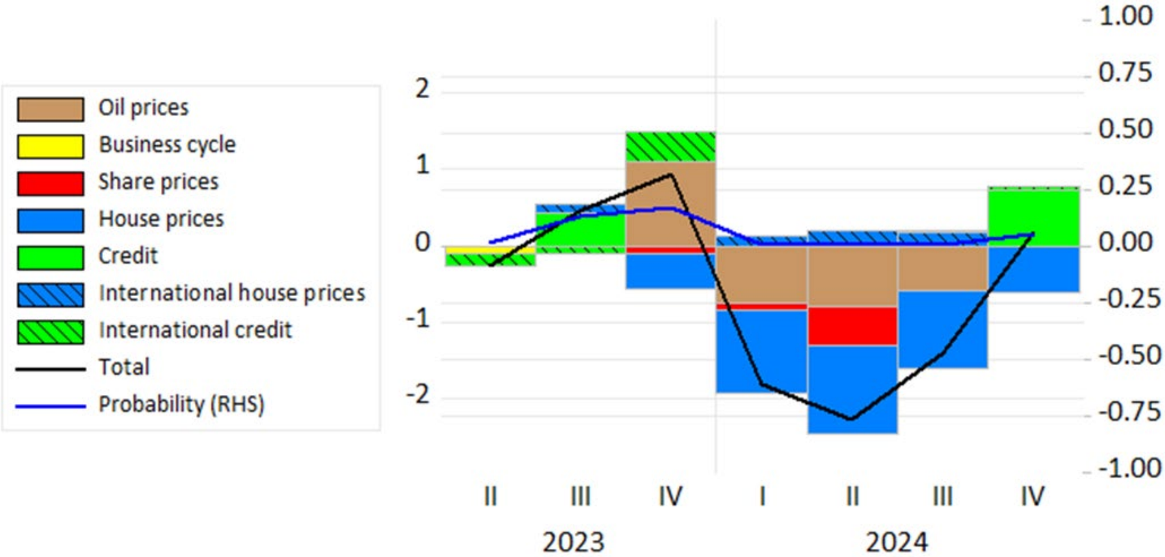
Italy

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
EAX_LTNFQ_D5(-3)	0.36 ***									1.4	3.3	0.5
OECD_RHP_G0(-2)	-0.84 ***									0.6	-0.4	-1.1
OECD_RSP_G1	-0.06 ***									9.0	-10.2	0.2
ITA_UNR_D1_3(-1)	1.12 ***									-0.1	0.5	-0.2
OECD_LTNFQ_D1_5(-4)		-0.35 ***								0.5	-1.8	-6.5
OECD_RSP_G1_5(-1)		-0.06 ***								3.5	-10.5	-0.1
ITA_UNR_D1_3(-2)		1.25 ***								-0.1	0.4	-0.2
EAX_LTNFQ_D5(-4)		0.34 ***								1.4	3.2	0.5
OECD_RHP_G0(-4)			-0.60 ***							0.6	-0.3	-1.1
EAX_LTNFQ_D5(-5)			0.36 ***							1.5	3.2	0.5
OECD_RSP_G0(-2)			-0.12 ***							2.3	-3.9	0.9
OECD_LBANFQ_D1_5(-5)			-0.59 ***							0.3	-1.3	-1.3
OECD_RSP_G0(-3)				-0.07 ***						2.2	-3.1	0.9
ITA_WPOIL_G3(-3)				0.06 ***						-0.6	13.1	34.1
OECD_LBANFQ_D5(-6)				0.92 ***						0.4	1.1	0.3
OECD_LBANFQ_D1_5(-6)				-0.74 ***						0.3	-1.2	-1.3
ITA_WPOIL_G3(-4)					0.04 ***					-0.8	13.3	34.1
EAX_LBANFQ_D3(-7)					0.79 ***					0.4	2.1	0.8
OECD_LBANFQ_D1_5(-7)					-0.91 ***					0.3	-1.0	-1.3
ITA_WPOIL_G3(-5)						0.05 ***				-0.7	12.6	34.1
OECD_LBANFQ_D1_3(-8)						-0.70 ***				0.3	-0.7	-1.6
OECD_LBANFQ_D5(-8)						0.92 ***				0.3	1.2	0.3
ITA_WPOIL_G3(-6)							0.05 ***			-0.6	11.8	34.1
OECD_LBANFQ_D0_3(-9)							-0.31 ***			0.4	-1.2	-1.9
OECD_LBANFQ_D5(-9)							1.01 ***			0.3	1.3	0.3
ITA_WPOIL_G3(-7)								0.03 ***		-0.4	11.0	34.1
OECD_LBANFQ_D3(-10)								0.72 ***		0.3	1.4	0.6
ITA_WPOIL_G3(-8)									0.02 ***	-0.2	10.0	34.1
OECD_LBANFQ_D3(-11)									0.81 ***	0.3	1.5	0.6
McFadden R2	0.59	0.58	0.54	0.52	0.52	0.42	0.4	0.27	0.3			
% of correct predictions	87.9	90.2	86.1	85.6	87.9	76.3	78.0	79.2	80.8			
No. of observations	173	173	173	173	173	173	173	173	172			



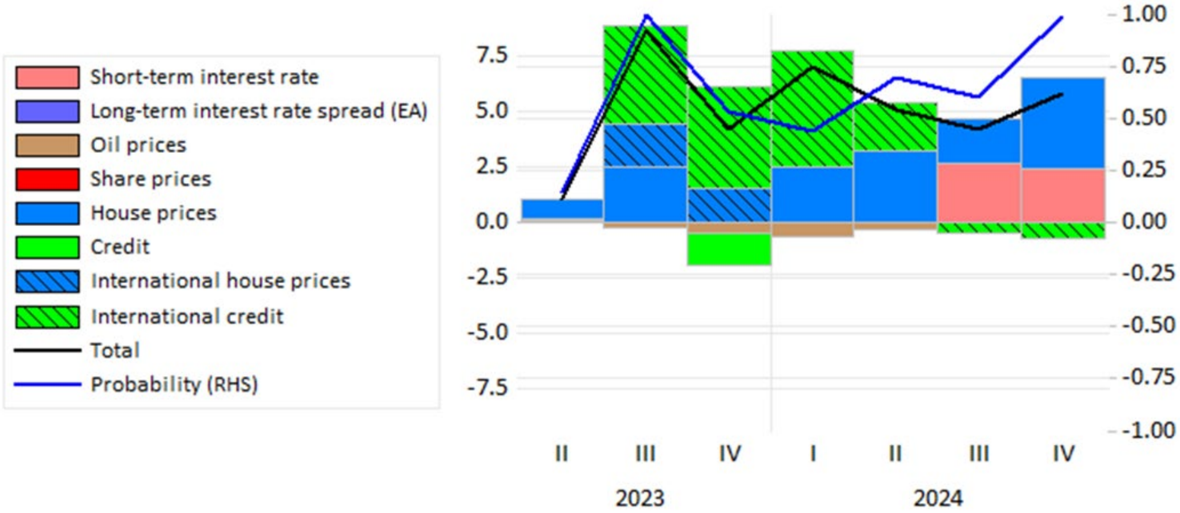
Japan

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
OECD_LBANFQ_D5(-3)	0.86 ***									0.4	1.0	0.3
JPN_TANKAN1	-0.04 ***									-4.0	-23.0	5.0
JPN_CAPU_D0_3	-0.06 ***									1.3	-13.0	-5.0
JPN_LBANFQ_D1_3(-4)		-0.21 ***								0.3	-1.1	-2.0
OECD_LBANFQ_D5(-4)		0.46 ***								0.4	1.1	0.3
OECD_RHP_G1(-3)		-0.13 ***								2.0	-0.6	1.0
JPN_RHP_G1(-4)			-0.13 ***							0.8	-1.4	4.4
OECD_LBANFQ_D1_5(-5)			-0.32 ***							0.1	-0.7	-1.3
JPN_RSP_G1_5(-2)			-0.04 ***							3.2	-11.4	4.6
JPN_WPOIL_G3(-2)			0.03 ***							0.5	13.5	34.1
JPN_WPOIL_G1(-3)				0.02 ***						4.8	24.6	-31.8
JPN_HPI_RPI_G1(-5)				-0.14 ***						0.3	-2.2	7.9
JPN_RSP_G1_5(-3)				-0.04 ***						3.0	-8.7	4.6
OECD_RHP_G1(-5)				-0.15 ***						1.9	-0.1	1.0
JPN_HPI_YDH_G1(-6)					-0.20 ***					-0.4	-2.5	5.3
OECD_RHP_G1(-6)					-0.23 ***					1.9	0.1	1.0
JPN_RSP_G0_5(-4)					-0.03 ***					7.4	-16.3	23.1
JPN_WPOIL_G1(-4)					0.02 ***					3.8	30.3	-31.8
OECD_RHP_G1(-7)						-0.20 ***				1.8	0.0	1.0
JPN_HPI_YDH_G1(-7)						-0.17 ***				-0.5	-2.6	5.3
JPN_WPOIL_G1(-5)						0.02 ***				3.6	28.9	-31.8
OECD_LBANFQ_D3(-8)						0.46 ***				0.4	1.2	0.6
JPN_LTNFQ_D1_3(-9)							-0.15 ***			0.4	-1.3	-4.8
JPN_HPI_RPI_G0(-8)							-0.45 ***			0.1	-0.8	1.4
OECD_LBANFQ_D3(-9)							0.81 ***			0.4	1.3	0.6
JPN_LTNFQ_D0(-10)								-0.21 **		0.4	-0.5	0.8
OECD_RHP_G1(-9)								-0.12 **		1.8	0.0	1.0
OECD_LTNFQ_D3(-10)								0.31 ***		1.3	2.4	1.1
OECD_RHP_G1(-10)									-0.09 *	1.7	0.1	1.0
OECD_LBANFQ_D3(-11)									0.47 ***	0.4	1.3	0.6
McFadden R2	0.4	0.23	0.32	0.33	0.4	0.33	0.29	0.19	0.15			
% of correct predictions	83.8	87.9	80.9	85.0	86.1	85.6	79.2	79.2	82.0			
No. of observations	173	173	173	173	173	173	173	173	172			



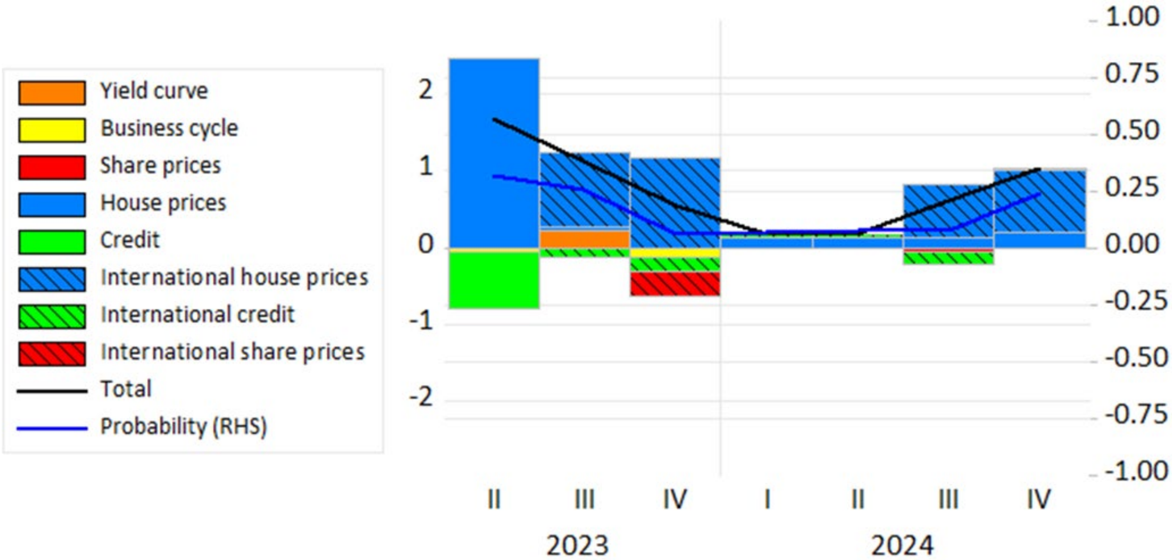
Netherlands

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
NLD_RSP_G1	-0.03 ***									8.5	-13.7	2.3
EAX_SPREAD	0.80 ***									-0.4	1.2	0.1
NLD_RHP_G1_5(-2)	-0.08 ***									1.1	-8.1	-10.6
EAX_LTNFQ_D1_3(-4)		-0.61 ***								0.3	-2.1	-7.5
OECD_RHP_G0(-3)		-1.22 ***								0.5	-0.4	-1.1
NLD_WPOIL_G5(-1)		0.11 ***								-0.1	13.1	-1.2
NLD_RHP_G1_3(-3)		-0.25 ***								0.7	-4.0	-10.5
OECD_RHP_G0(-4)			-0.96 ***							0.5	-0.2	-1.1
NLD_LTNFQ_D3(-5)			0.20 ***							3.3	7.3	-4.0
EAX_LTNFQ_D1_3(-5)			-0.64 ***							0.3	-1.9	-7.5
NLD_WPOIL_G5(-2)			0.19 ***							-0.2	14.6	-1.2
OECD_LBANFQ_D5(-6)				2.07 ***						0.4	1.0	0.3
OECD_LTNFQ_D1_3(-6)				-0.85 ***						0.3	-1.5	-6.7
NLD_RHP_G1_5(-5)				-0.24 ***						0.6	-7.3	-10.6
NLD_WPOIL_G5(-3)				0.27 ***						-0.2	15.1	-1.2
OECD_LTNFQ_D0_5(-7)					-0.38 ***					0.5	-2.3	-5.6
EAX_LBANFQ_D3(-7)					0.90 ***					0.5	1.9	0.8
NLD_WPOIL_G5(-4)					0.13 ***					-0.2	13.6	-1.2
NLD_RHP_G1_3(-6)					-0.31 ***					0.4	-5.3	-10.5
NLD_IRS_D1_5(-5)						0.89 ***				-0.1	1.2	3.0
OECD_LBANFQ_D3(-8)						1.01 ***				0.4	1.3	0.6
EAX_LTNFQ_D3(-8)						0.67 ***				1.5	3.6	0.9
NLD_RHP_G1_5(-7)						-0.19 ***				0.3	-6.4	-10.6
NLD_IRS_D1_5(-6)							0.83 ***			-0.1	1.3	3.0
EAX_LTNFQ_D5(-9)							0.69 ***			1.6	3.1	0.5
OECD_LBANFQ_D3(-9)							1.16 ***			0.4	1.3	0.6
NLD_RHP_G0_3(-8)							-0.16 ***			0.6	-8.1	-25.4
EAX_SPREAD(-7)								0.69 ***		-0.3	0.7	0.1
NLD_IRS_D0_3(-7)								0.20 ***		-0.3	2.0	1.8
OECD_LBANFQ_D3(-10)								0.83 ***		0.4	1.3	0.6
NLD_RHP_G1_3(-9)								-0.14 ***		0.2	-5.1	-10.5
EAX_SPREAD(-8)									0.48 ***	-0.2	0.7	0.1
NLD_RHP_G1_3(-10)									-0.12 ***	0.2	-4.4	-10.5
OECD_LBANFQ_D3(-11)									0.74 ***	0.4	1.3	0.6
McFadden R2	0.53	0.68	0.69	0.7	0.59	0.61	0.62	0.48	0.37			
% of correct predictions	91.3	91.9	93.0	92.4	91.1	91.3	92.5	84.4	82.6			
No. of observations	173	172	171	170	169	173	173	173	172			



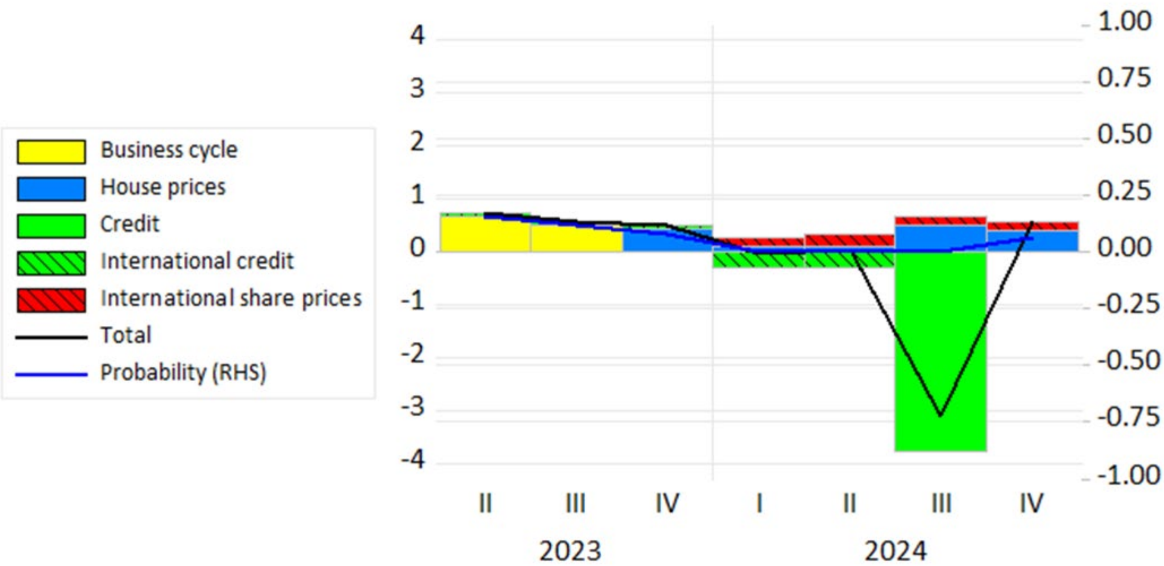
New Zealand

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
NZL_LTNFQ_D5(-3)	0.16 ***									2.7	5.8	-1.6
NZL_CAPU_D1_3	-0.36 ***									0.2	-1.7	0.1
NZL_RHP_G0_5(-2)	-0.10 ***									2.4	-10.2	-24.3
OECD_RHP_G0(-3)		-0.61 ***								0.5	-0.1	-1.1
NZL_RHP_G5(-3)		0.11 ***								3.0	6.4	3.7
OECD_LTNFQ_D3(-4)		0.32 ***								1.4	2.7	1.1
NZL_YC(-1)		-0.24 ***								-0.2	-2.1	-1.4
OECD_RHP_G0(-4)			-0.75 ***							0.5	0.0	-1.1
OECD_RSP_G5(-2)			0.08 ***							4.3	8.0	0.3
NZL_GDPV_CAP_G5(-3)			0.72 ***							1.3	1.9	1.1
OECD_LTNFQ_D3(-5)			0.50 ***							1.4	2.7	1.1
NZL_RHP_G3(-5)				0.09 ***						3.2	6.9	4.7
OECD_LBANFQ_D3(-6)				0.61 ***						0.4	1.4	0.6
NZL_RHP_G3(-6)					0.10 ***					3.0	7.3	4.7
OECD_LBANFQ_D3(-7)					0.55 ***					0.4	1.3	0.6
OECD_RHP_G1_5(-7)						-0.20 ***				0.3	-0.6	-3.2
NZL_RSP_G5(-5)						0.09 ***				0.6	6.1	0.0
OECD_LTNFQ_D3(-8)						0.40 ***				1.3	2.4	1.1
NZL_RHP_G3(-7)						0.09 ***				2.8	7.7	4.7
OECD_RHP_G0(-8)							-0.51 ***			0.4	0.1	-1.1
OECD_LBANFQ_D3(-9)							0.38 ***			0.4	1.0	0.6
NZL_RHP_G3(-8)							0.15 ***			2.7	8.0	4.7
NZL_UNR_D1(-8)								0.80 ***		0.1	0.5	0.2
OECD_LBANFQ_D3(-10)								0.55 ***		0.4	0.9	0.6
NZL_GDPV_CAP_G3(-8)								0.73 ***		1.3	2.1	1.7
NZL_RHP_G3(-9)								0.13 ***		2.5	8.2	4.7
NZL_RSP_G5(-8)									0.06 ***	0.2	5.3	0.0
NZL_WPOIL_G5(-8)									0.05 ***	0.2	7.7	-1.2
NZL_UNR_D1_3(-9)									0.81 ***	-0.1	0.5	0.4
NZL_RHP_G0_3(-10)									-0.06 ***	1.3	-5.1	-25.3
McFadden R2	0.46	0.37	0.35	0.22	0.22	0.3	0.28	0.35	0.33			
% of correct predictions	87.3	86.1	84.4	78.0	80.9	80.9	85.6	82.7	81.8			
No. of observations	173	173	173	173	173	173	173	173	165			



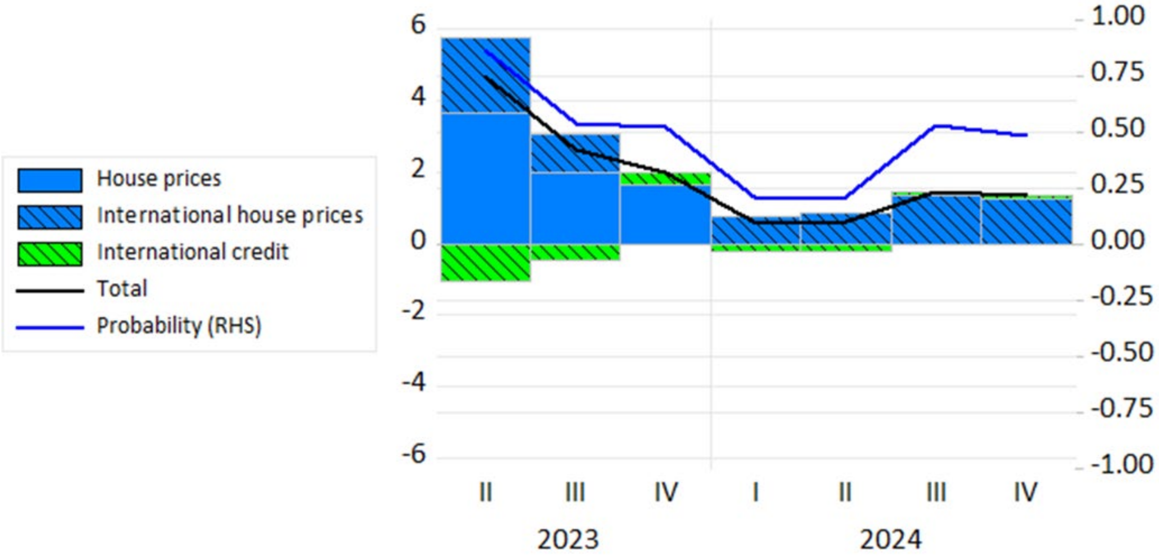
Norway

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
OECD_LBANFQ_D3(-3)	0.77 ***									0.4	1.4	0.6
NOR_CAPU_D1	-0.32 ***									0.2	-2.3	-2.3
OECD_LBANFQ_D3(-4)		0.77 ***								0.4	1.4	0.6
NOR_CAPU_D1(-1)		-0.24 ***								0.1	-2.1	-2.3
NOR_HPI_RPI_G3(-4)			0.10 ***							2.3	7.4	4.3
NOR_HPI_RPI_G1_3(-4)			-0.07 ***							1.0	-4.9	-4.2
OECD_LBANFQ_D3(-5)			0.82 ***							0.4	1.4	0.6
OECD_RSP_G3(-3)				0.09 ***						3.9	11.0	6.5
OECD_LTNFQ_D3(-6)				0.83 ***						1.3	2.7	1.1
NOR_HPI_YDH_G5(-5)				0.27 ***						0.6	5.2	1.6
OECD_LTNFQ_D3(-7)					0.84 ***					1.3	2.6	1.1
NOR_HPI_YDH_G5(-6)					0.25 ***					0.6	5.1	1.6
OECD_RSP_G3(-4)					0.12 ***					3.6	12.8	6.5
NOR_LTNFQ_D3(-8)						0.21 ***				2.4	6.5	-14.8
OECD_RSP_G3(-5)						0.10 ***				3.3	14.2	6.5
NOR_HPI_YDH_G3(-7)						0.20 ***				0.2	7.7	3.7
NOR_HPI_YDH_G3(-8)							0.15 ***			0.2	7.7	3.7
OECD_RSP_G3(-6)							0.10 ***			3.2	14.8	6.5
NOR_YC(-7)								-0.50 ***		0.1	-0.9	-0.1
OECD_RSP_G3(-7)								0.12 ***		3.1	14.8	6.5
NOR_GDPV_CAP_G5(-9)									0.44 ***	1.8	2.9	1.2
OECD_RSP_G3(-8)									0.08 ***	3.2	14.1	6.5
McFadden R2	0.4	0.37	0.42	0.51	0.56	0.59	0.48	0.41	0.31			
% of correct predictions	83.0	84.3	83.9	87.8	88.4	87.0	85.1	81.5	76.9			
No. of observations	141	140	161	156	155	162	161	173	173			



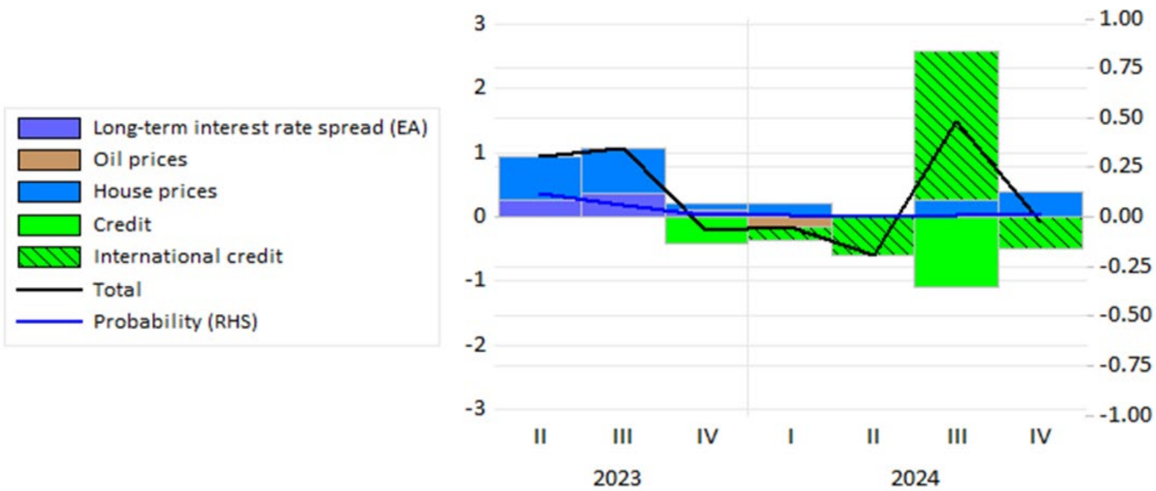
Portugal

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
EAX_LTNFQ_D5(-3)	0.90 ***									1.5	3.1	0.5
OECD_RHP_G0(-2)	-1.35 ***									0.6	-0.4	-1.1
PRT_RHP_G0_5(-2)	-0.28 ***									1.6	-5.2	-13.0
EAX_LTNFQ_D3(-4)		0.55 ***								1.5	3.4	0.9
PRT_RHP_G0_5(-3)		-0.15 ***								1.4	-4.8	-13.0
OECD_RHP_G0(-3)		-0.70 ***								0.6	-0.4	-1.1
OECD_LBANFQ_D5(-5)			1.50 ***							0.4	1.1	0.3
PRT_RHP_G0_3(-4)			-0.14 ***							1.1	-3.2	-11.9
OECD_LBANFQ_D1_5(-5)			-0.50 ***							0.3	-1.0	-1.3
EAX_LTNFQ_D3(-6)				0.28 ***						1.4	3.5	0.9
OECD_RHP_G1_5(-5)				-0.22 ***						0.7	-2.3	-3.2
EAX_LTNFQ_D3(-7)					0.29 ***					1.4	3.6	0.9
OECD_RHP_G1_5(-6)					-0.24 ***					0.8	-2.4	-3.2
EAX_LBANFQ_D3(-8)						0.40 ***				0.4	2.1	0.8
OECD_RHP_G0_5(-7)						-0.15 ***				0.9	-2.7	-8.7
OECD_RHP_G0_5(-8)							-0.14 ***			0.9	-2.6	-8.7
EAX_LBANFQ_D3(-9)							0.46 ***			0.4	2.1	0.8
EAX_LBANFQ_D3(-10)								0.48 ***		0.3	2.2	0.8
OECD_RHP_G0_5(-9)								-0.16 ***		0.9	-2.8	-8.7
PRT_GDPV_CAP_G1_3(-9)									-0.33 ***	0.0	-1.0	-0.4
PRT_WPOIL_G3(-8)									0.03 ***	-0.4	11.3	34.1
OECD_LBANFQ_D3(-11)									0.78 ***	0.3	1.4	0.6
McFadden R2	0.65	0.54	0.56	0.31	0.34	0.3	0.31	0.34	0.36			
% of correct predictions	84.0	88.1	86.4	79.8	80.9	81.5	79.8	80.4	80.8			
No. of observations	119	118	125	173	173	173	173	173	172			



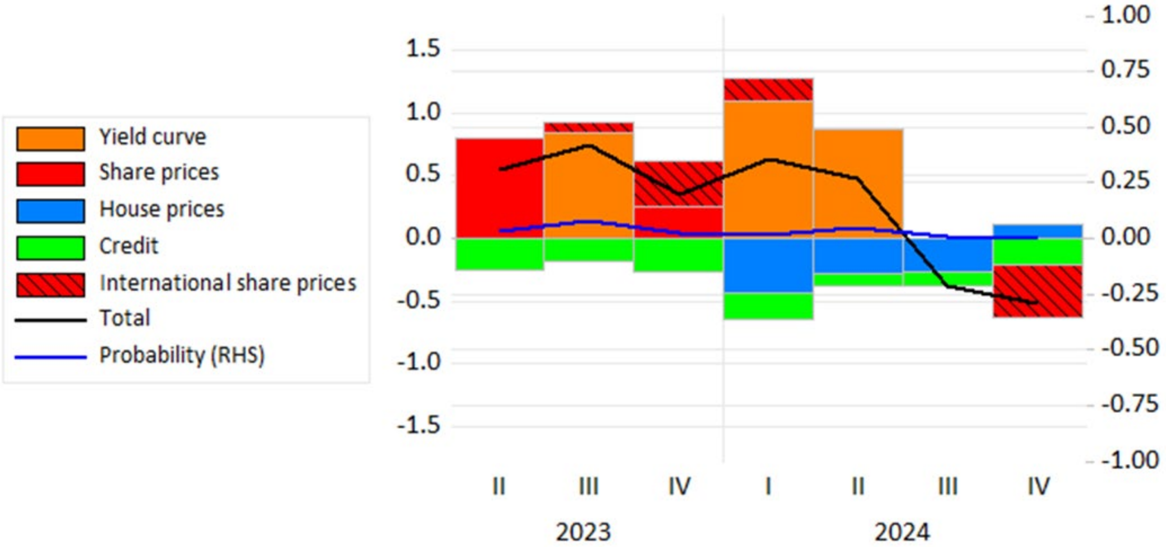
Spain

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
EAX_SPREAD	1.97 ***									-0.4	1.0	0.1
ESP_HPI_YDH_G1_5(-2)	-0.19 ***									0.7	-6.8	-4.2
EAX_SPREAD(-1)		2.67 ***								-0.4	1.0	0.1
ESP_HPI_YDH_G0_5(-3)		-0.16 ***								1.2	-8.8	-5.0
ESP_RHP_G0_5(-4)			-0.07 ***							1.7	-10.0	-1.6
EAX_SPREAD(-2)			0.72 ***							-0.4	1.0	0.1
ESP_LBANFQ_D5(-5)			0.13 ***							-0.4	7.5	-2.6
ESP_RHP_G1_5(-5)				-0.09 ***						1.2	-7.3	-2.1
ESP_WPOIL_G5(-3)				0.06 ***						-0.4	11.8	-1.2
OECD_LBANFQ_D5(-6)				0.99 ***						0.3	1.5	0.3
ESP_HPI_RPI_G1_5(-6)					-0.09 ***					0.8	-6.9	0.1
EAX_LTNFQ_D5(-7)					0.36 ***					1.5	3.7	0.5
OECD_LBANFQ_D5(-7)					0.79 ***					0.3	1.5	0.3
OECD_LBANFQ_D1_3(-8)						-1.50 ***				0.2	-0.6	-1.6
ESP_HPI_YDH_G5(-7)						0.20 ***				0.6	5.5	2.9
ESP_LTNFQ_D5(-8)						0.27 ***				0.7	9.9	-2.3
ESP_HPI_YDH_G1_5(-8)							-0.11 ***			0.6	-5.8	-4.2
EAX_LTNFQ_D5(-9)							0.44 ***			1.4	3.6	0.5
OECD_LBANFQ_D3(-9)							0.48 ***			0.3	1.6	0.6
ESP_HPI_YDH_G5(-9)								0.15 ***		0.4	6.4	2.9
EAX_LTNFQ_D5(-10)								0.92 ***		1.4	3.6	0.5
ESP_HPI_YDH_G1_5(-9)								-0.18 ***		0.7	-6.1	-4.2
ESP_WPOIL_G5(-8)									0.04 ***	-0.5	11.1	-1.2
OECD_LBANFQ_D3(-11)									1.25 ***	0.3	1.8	0.6
McFadden R2	0.68	0.74	0.54	0.48	0.47	0.56	0.49	0.57	0.52			
% of correct predictions	92.4	93.1	89.0	85.9	89.6	84.9	85.6	87.1	92.7			
No. of observations	131	130	173	170	173	126	125	124	165			



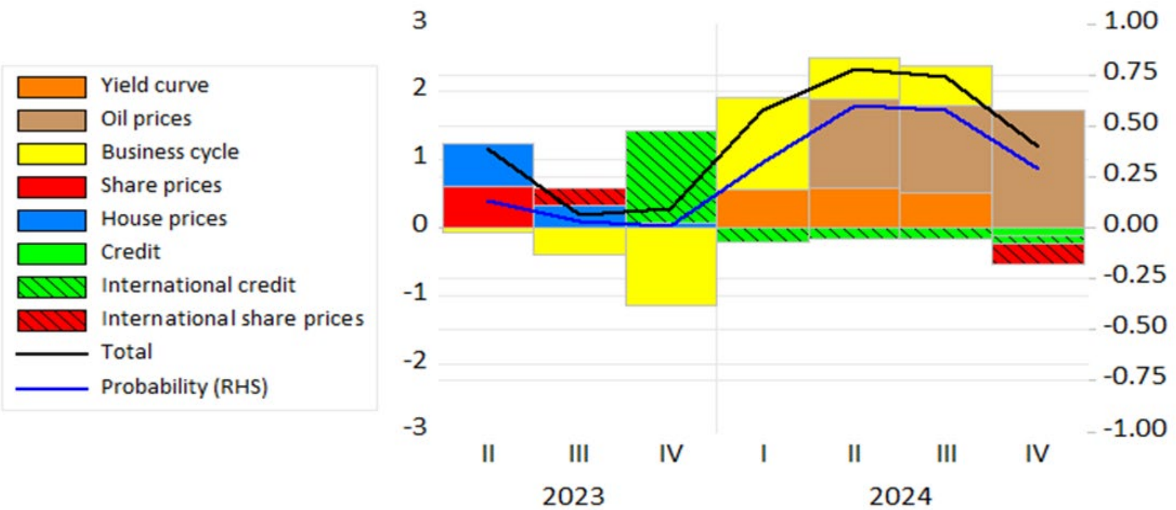
Sweden

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
SWE_RSP_G1	-0.05 ***									15.9	-16.3	-5.8
SWE_LBANFQ_D5(-3)	0.45 ***									0.9	4.8	0.8
OECD_RSP_G1_5(-1)		-0.06 ***								3.4	-13.7	-0.1
SWE_LBANFQ_D5(-4)		0.34 ***								0.9	4.7	0.8
SWE_YC(-1)		-0.45 ***								0.9	-0.7	-1.2
OECD_RSP_G1_3(-2)			-0.05 ***							2.6	-9.8	-6.3
SWE_RSP_G0(-2)			-0.08 ***							3.8	-5.8	-0.9
SWE_LBANFQ_D5(-5)			0.49 ***							0.9	4.6	0.8
OECD_RSP_G0_3(-3)				-0.03 ***						5.2	-13.6	-2.9
SWE_HPI_YDH_G3(-5)				0.30 ***						0.1	4.7	-0.7
SWE_YC(-3)				-0.58 ***						0.9	-0.6	-1.2
SWE_LBANFQ_D5(-6)				0.39 ***						0.9	4.6	0.8
SWE_HPI_YDH_G3(-6)					0.19 ***					0.0	4.9	-0.7
SWE_YC(-4)					-0.46 ***					0.9	-0.4	-1.2
SWE_LBANFQ_D3(-7)					0.29 ***					0.8	5.7	1.1
SWE_HPI_YDH_G3(-7)						0.18 ***				0.0	5.1	-0.7
SWE_LBANFQ_D3(-8)						0.36 ***				0.8	5.8	1.1
SWE_HPI_RPI_G5(-8)							0.21 ***			0.6	4.9	1.8
OECD_RSP_G5(-6)							0.11 ***			3.7	9.0	0.3
SWE_LBANFQ_D5(-9)							0.39 ***			0.9	4.5	0.8
SWE_IRS_D1_3(-7)								0.38 ***		-0.1	0.8	2.3
SWE_HPI_RPI_G5(-9)								0.19 ***		0.6	4.7	1.8
OECD_RSP_G5(-7)								0.10 ***		3.6	9.1	0.3
SWE_LBANFQ_D5(-10)								0.40 ***		0.9	4.4	0.8
SWE_IRS_D1_3(-8)									0.38 ***	-0.1	0.8	2.3
SWE_HPI_YDH_G3(-10)									0.17 ***	0.0	4.9	-0.7
SWE_LBANFQ_D5(-11)									0.34 ***	0.9	4.3	0.8
McFadden R2	0.57	0.57	0.56	0.64	0.55	0.5	0.51	0.5	0.43			
% of correct predictions	86.1	88.4	87.9	90.8	90.8	89.0	85.0	87.0	78.6			
No. of observations	173	173	173	173	173	173	173	146	145			



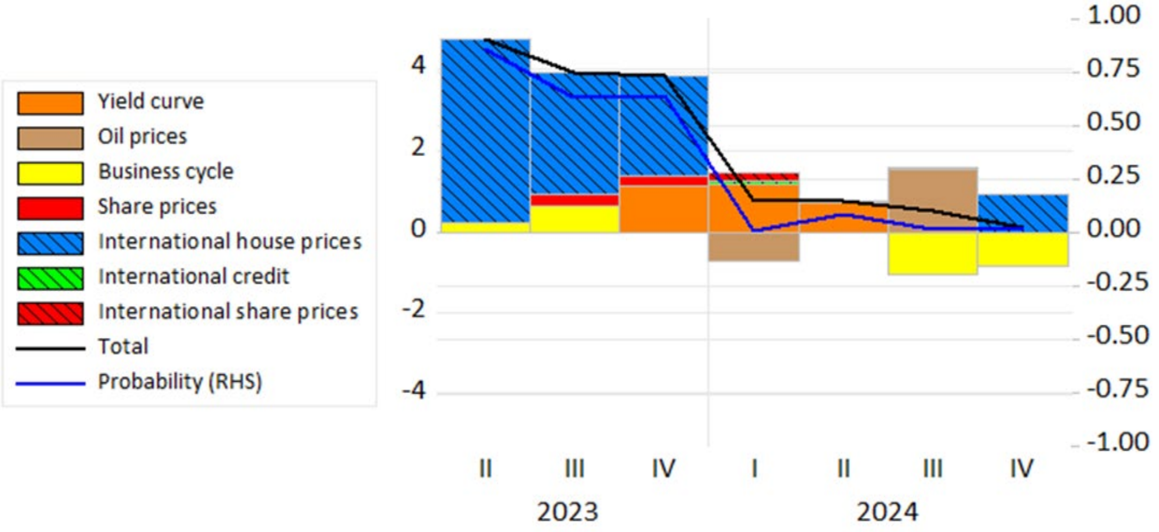
Switzerland

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
CHE_HPI_RPI_G0_5(-2)	-0.13 ***									1.6	-6.4	-4.1
CHE_RSP_G1	-0.06 ***									9.5	-14.2	-4.0
CHE_GDPV_CAP_G0_5(-1)	-0.22 ***									0.7	-3.5	0.5
CHE_RHP_G1_5(-3)		-0.17 ***								0.9	-2.9	-1.5
CHE_GDPV_CAP_G5(-2)		0.81 ***								0.9	1.8	**0.5**
OECD_RSP_G0(-1)		-0.09 ***								2.4	-5.3	0.9
OECD_RSP_G1(-1)		-0.04 ***								8.8	-12.0	0.2
CHE_HPI_RPI_G1_5(-4)			-0.10 ***							1.0	-3.1	-0.1
OECD_LBANFQ_D1_3(-5)			-0.88 ***							0.2	-0.8	-1.6
CHE_GDPV_CAP_G5(-3)			2.31 ***							0.9	1.9	0.5
CHE_HPI_YDH_G1_5(-5)				-0.16 ***						0.8	-2.1	0.4
CHE_UNR_D5(-4)				-6.27 ***						0.1	-0.1	-0.1
OECD_LTNFQ_D5(-6)				0.46 ***						1.2	2.4	0.9
CHE_YC(-3)				-0.55 ***						0.8	-0.9	-0.4
CHE_UNR_D5(-5)					-2.87 ***					0.1	-0.1	-0.1
CHE_WPOIL_G3(-4)					0.04 ***					-0.4	13.2	34.1
OECD_LTNFQ_D3(-7)					0.46 ***					1.2	2.8	1.1
CHE_YC(-4)					-0.59 ***					0.8	-1.0	-0.4
CHE_UNR_D5(-6)						-2.74 ***				0.1	-0.1	-0.1
CHE_WPOIL_G3(-5)						0.04 ***				-0.5	13.2	34.1
OECD_LTNFQ_D3(-8)						0.46 ***				1.2	2.8	1.1
CHE_YC(-5)						-0.51 ***				0.8	-0.9	-0.4
CHE_LBANFQ_D5(-9)							0.39 ***			1.6	2.5	1.4
OECD_RSP_G5(-6)							0.08 ***			3.8	8.5	0.3
CHE_WPOIL_G3(-6)							0.05 ***			-0.4	12.6	34.1
OECD_LTNFQ_D3(-9)							0.35 ***			1.2	2.8	1.1
CHE_UNR_D3(-8)								-2.29 ***		0.1	-0.2	0.0
CHE_WPOIL_G1(-7)								0.01 ***		0.9	30.6	-31.8
OECD_LBANFQ_D5(-10)								0.73 ***		0.4	1.1	0.3
CHE_YC(-7)								-0.48 ***		0.8	-0.5	-0.4
CHE_RSP_G5(-8)									0.07 ***	3.8	8.1	3.7
CHE_RHP_G3(-10)									0.19 ***	0.8	3.7	5.3
CHE_WPOIL_G1(-8)									0.01 ***	0.6	27.5	-31.8
OECD_LTNFQ_D3(-11)									0.26 ***	1.2	2.6	1.1
McFadden R2	0.62	0.55	0.58	0.55	0.54	0.52	0.44	0.46	0.35			
% of correct predictions	91.3	89.6	87.3	90.5	88.1	90.4	86.1	89.0	87.2			
No. of observations	173	173	173	169	168	167	173	173	172			



United Kingdom

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
GBR_GDPV_CAP_G1_5(-1)	-0.48 ***									0.3	-3.5	-0.1
OECD_RHP_G0_3(-2)	-0.46 ***									0.5	-4.3	-9.8
GBR_GDPV_CAP_G0_3(-1)	-0.39 ***									0.9	-4.2	0.1
GBR_RSP_G1_5(-1)		-0.12 ***								2.1	-16.5	-1.4
GBR_UNR_D0_3(-2)		0.95 ***								-0.1	1.3	0.6
OECD_RHP_G0_5(-3)		-0.34 ***								0.7	-4.7	-8.7
OECD_RHP_G0_5(-4)			-0.28 ***							0.6	-3.5	-8.7
GBR_YC(-2)			-0.81 ***							0.7	-1.4	-0.9
GBR_RSP_G1_5(-2)			-0.10 ***							2.0	-16.1	-1.4
OECD_RSP_G0_3(-3)				-0.04 ***						4.8	-18.4	-2.9
GBR_WPOIL_G1(-3)				0.02 ***						3.6	39.0	-31.8
OECD_LBANFQ_D3(-6)				0.89 ***						0.4	1.7	0.6
GBR_YC(-3)				-0.85 ***						0.7	-1.7	-0.9
OECD_LBANFQ_D3(-7)					0.67 ***					0.4	1.6	0.6
GBR_YC(-4)					-0.51 ***					0.7	-1.7	-0.9
GBR_WPOIL_G3(-5)						0.05 ***				0.6	11.2	34.1
GBR_GDPV_CAP_G3(-6)						0.91 ***				1.3	2.9	0.3
OECD_LBANFQ_D3(-8)						0.77 ***				0.4	1.4	0.6
OECD_RHP_G5(-8)							0.36 ***			1.2	3.1	4.2
GBR_GDPV_CAP_G3(-7)							0.70 ***			1.4	3.0	0.3
GBR_GDPV_CAP_G3(-8)								0.38 **		1.4	2.9	0.3
OECD_RHP_G3(-9)								0.25 ***		1.3	3.9	5.4
GBR_WPOIL_G1_3(-8)									-0.03 ***	4.0	-7.1	-65.9
GBR_RSP_G3(-8)									0.08 ***	2.9	7.4	2.3
OECD_RHP_G5(-10)									0.47 ***	1.2	3.0	4.2
GBR_GDPV_CAP_G3(-9)									0.73 ***	1.4	2.8	0.3
McFadden R2	0.77	0.73	0.7	0.67	0.41	0.43	0.32	0.24	0.43			
% of correct predictions	96.0	96.0	94.8	92.5	89.0	83.8	80.9	78.0	86.1			
No. of observations	173	173	173	173	173	173	173	173	173			



United States

Variable	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Non-downturn	Downturn	Latest
USA_RSP_G1	-0.05 ***									7.2	-15.4	-1.3
USA_CAPU_D0_5	-0.23 ***									0.7	-7.8	2.2
OECD_RSP_G0_5(-1)		-0.03 ***								5.2	-25.2	3.3
USA_CAPU_D0_5(-1)		-0.15 ***								0.6	-6.5	2.2
OECD_LTNFQ_D3(-5)			0.84 ***							1.4	3.0	1.1
USA_YC(-2)			-0.83 ***							1.3	-0.5	-1.7
OECD_LTNFQ_D3(-6)				0.70 ***						1.4	2.9	1.1
USA_YC(-3)				-0.75 ***						1.3	-0.5	-1.7
OECD_LTNFQ_D3(-7)					0.55 ***					1.4	2.6	1.1
USA_YC(-4)					-0.67 ***					1.3	-0.6	-1.7
USA_INDPRO_G3(-6)						0.60 ***				1.7	3.0	0.8
USA_RHP_G5(-7)						0.48 ***				1.3	3.3	6.2
USA_UNR_D0_3(-6)						0.80 ***				0.1	-1.2	-0.3
USA_HPI_YDH_G1_5(-7)						-0.24 ***				0.4	-2.3	0.7
OECD_RHP_G5(-8)							0.46 ***			1.3	2.8	4.2
USA_INDPRO_G3(-7)							0.61 ***			1.8	3.2	0.8
USA_HPI_RPI_G1_3(-8)							-0.28 ***			0.3	-2.3	-7.2
USA_HPI_RPI_G1_3(-9)								-0.22 ***		0.2	-1.5	-7.2
USA_RHP_G5(-9)								0.54 ***		1.2	3.5	6.2
USA_INDPRO_G3(-8)								0.59 ***		1.8	3.5	0.8
USA_CAPU_D3(-8)									0.54 ***	-0.2	1.4	4.8
USA_YC(-8)									-0.55 ***	1.3	-0.4	-1.7
McFadden R2	0.54	0.39	0.47	0.44	0.39	0.43	0.44	0.4	0.37			
% of correct predictions	89.6	90.2	88.4	87.3	85.6	89.6	89.0	85.6	88.4			
No. of observations	173	173	173	173	173	173	173	173	173