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Home, safe home: cross-country monitoring framework for vulnerabilities in the residential real estate sector

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Abstract

This paper proposes a framework for monitoring vulnerabilities related to the residential real estate sector in a cross-country context. The framework might be useful for complementing or cross-checking signals available from existing approaches. It takes into account three dimensions of real estate sector vulnerabilities (i.e. valuation, household indebtedness and the bank credit cycle) and enables monitoring across countries in a simple and informative way. Indicators are derived from the early warning literature and policy publications. They are aggregated in a model-free way to a vulnerability measure, explicitly capturing the level and the dynamics of vulnerabilities. The measure proves to be a significant predictor of historical real estate crises, with a better forecasting performance than the majority of advantageously in-sample calibrated model-based estimates. The monitoring framework allows for a simple and transparent analysis across different dimensions, provides a cross-check of consistency of signals from several indicators, and accounts for the developments in terms of the levels and dynamics. In view of its good forecasting performance, it is a useful complement of model-based toolkits for analysing vulnerabilities in the residential real estate sector.

Keywords:	real estate vulnerabilities; real estate crises; early warning models; risk monitoring;
JEL classification:	R31; E32; C53;

Non-technical summary

This paper develops a simple and transparent framework for monitoring vulnerabilities related to the residential real estate sector, which might be useful for complementing or cross-checking signals available from existing approaches. The approach uses a selection of key indicators which account for three main dimensions of the real estate sector vulnerabilities, i.e., valuation (overvaluation, price-to-income and price-to-rent ratios), the resilience of the household sector (households debt service ratio, debt-to-income ratio, household leverage) and the credit cycle of the banking system (credit for house purchases to GDP, lending spreads, loan-to-deposit ratio). The choice of indicators is based on the variables identified in the early warning literature on residential real estate vulnerabilities, combined with additional indicators that have been highlighted by various policy bodies as important monitoring metrics for this sector.

The monitoring approach presented in this paper is not based on model-calibrated variable selection which would claim to provide the best possible early warning system for residential real estate crises. Instead, it seeks to combine relevant variables in a broad measure, capturing three main dimensions of real estate-related vulnerabilities. The indicators are first standardised, in order to offer a possibility of a cross-country reference. For summary purposes, they are then aggregated into one composite vulnerability measure. This measure proves to be an informative predictor of residential real estate-related crises. For example, a vulnerability map created by using the measure as of end-2006 highlights most of the countries affected by residential real estate crises in the three subsequent years. In a broader quantitative comparison, the measure performs better than most model-based indicator estimates, even when models are calibrated on favourable in-sample conditions. In fact, out of all possible models with three-variable combinations, our vulnerability measure is one of the top forecasting performers, beating also some of the models which have a larger set of variables. The aggregate measure is also robust to the definition of crisis periods.

From the policy perspective, the proposed simple model-free vulnerability measure offers several advantages: it is transparent and easy to interpret, while also avoiding model uncertainty and threshold effects. The monitoring in this context allows for an analysis of vulnerabilities across different dimensions, provides a cross-check of consistency of signals from several indicators, and accounts for the developments in terms of the levels and dynamics. In view of some constraints of model-based estimates (e.g., the number of included factors given the scarcity of observed crises events and correlation structures), the model-free vulnerability measure is a useful complement of model-based tools for monitoring real estate vulnerabilities.

1 Simple framework for cross-country monitoring of vulnerabilities in the residential real estate sector

Crises related to the vulnerabilities in the residential real estate sector have been quite common throughout history. While the underlying causes and triggers have differed, these crises tend to be characterised by negative feedback loops between falling house prices, reduced household spending, bank losses and credit contraction. The consequences for the real economy are typically severe, not least given the importance of real estate in the balance sheets of households and credit institutions.[1]

In view of these effects, preventing the build-up of vulnerabilities in residential real estate is an important objective of economic policy. In recent years, macroprudential authorities have been established in many countries to enhance the resilience of the financial system and prevent or mitigate the build-up of financial imbalances.[2] This responsibility requires monitoring tools which deliver accurate, timely, reliable and easily interpretable signals of vulnerabilities across financial and real sectors.[3] Macroprudential authorities, as well as other institutions, are indeed equipped with such toolkits, as documented in recent years in a number of policy publications (see, e.g., International Monetary Fund (2017), Organisation for Economic Cooperation and Development (2017), Euro-

[1]Two thirds of house price booms have ended up in recessions (see also Cerutti, Dagher, and DellAriccia (2015)). Recessions accompanied by housing busts typically last longer and are associated with higher output losses. On average, recessions with housing busts have led to a 3.2% GDP loss and a 1.8% unemployment increase, compared to 2% GDP loss and 0.8% increase in unemployment for recessions without housing problems (see also Claessens, Kose, and Terrones (2008)). For further information on real estate crises, see Cecchetti (2008), Reinhart and Rogoff (2010), Ferrari, Pirovano, and Cornacchia (2015), Hartmann (2015), Bordo and Jeanne (2002), Reinhart and Rogoff (2008), Crowe et al. (2013), World Economic Forum (2015), Mian and Sufi (2014), and Wachter, Cho, and Joong Tcha (2014). A build-up of vulnerabilities in the real estate sector is particularly important in the current context of persisting low interest rates (see also European Systemic Risk Board (2016a)). One of recent press releases of the ESRB General Board (24 September 2015) emphasises that the " (...) global environment of low interest rates and low risk premia, while necessary to support the still sluggish nominal growth, is one common driver of the current risk situation and may have unintended effects on some economic sectors or in some countries that may require the adoption of targeted macroprudential measures". Similarly, European Central Bank (2015) suggests that price growth in residential real estate needs monitoring, especially when accompanied by increased leverage, against the backdrop of the current accommodative monetary policy.

[2]See for instance Bank of England (2009); Committee on the Global Financial System (2010); Borio (2011); Financial Stability Board, International Monetary Fund, and Bank for International Settlements (2011) and International Monetary Fund (2011). For an example of recent policy work in the area of the residential real estate sector stability, see European Systemic Risk Board (2016c).

[3]See, for instance, European Systemic Risk Board (2014, 2016b).

pean Systemic Risk Board (2016b, 2016c), and European Central Bank (2016, 2015)). This paper proposes a simple and intuitive monitoring framework which might be a useful complement for cross-checking signals derived from existing toolkits.[4]

The rich and growing literature on forward-looking assessment of vulnerabilities related to systemic risk is focused on so-called early warning models.[5] These models aim to find indicators which provide early and accurate signals of potential banking or financial crises within certain time horizons. Specifically on vulnerabilities in the residential real estate sector, a number of recent studies document early warning properties of various indicators. In particular, downturns in real estate prices can be forecasted using general economic developments, changes in credit conditions and interest rates (e.g., Agnello and Schuknecht (2011), Alessi and Detken (2011), Borgy, Clerc, and Renne (2009), Gerdesmeier, Lenarčič, and Roffia (2012), Claessens, Kose, and Terrones (2008)). Other early warning models rely on indicators more specific to the real estate sector, such as estimates of over-/undervaluation of residential property prices (European Systemic Risk Board (2016b)), debt service ratio (Drehmann and Juselius (2012)), price-to-rent and price-to-income ratios (Borio and Drehmann (2009), Drehmann et al. (2010), Mendoza and Terrones (2008), Riiser (2005)), and credit for house purchases (Büyükkarabacaka and Valev (2010)).

From a policy makers' perspective, early warning models are very useful since they enable the risk identification and thus application of policy tools at an early stage, which is likely to be more effective in curbing systemic risk. At the same time, an important shortcoming of early warning models for monitoring purposes is the estimation uncertainty, including coefficient significance and stability over time. These shortcomings result from inevitable limitations related to the difficulties of modelling with relatively complex methodologies on small crisis samples, limited time series and cross-sectional

[4]The approach to measuring real estate vulnerabilities developed in this paper is not related to any of the institutional approaches, as quoted above. In particular, the approach of this paper is not related to the methodology underlying the warnings of the European Systemic Risk Board on the vulnerabilities in the residential real estate sector (see European Systemic Risk Board (2016c) and European Central Bank (2016)).

[5]For a discussion, see Barrell, Dilruba, and Liadz (2010). See also Drehmann, Borio, and Tsatsaronis (2011), International Monetary Fund (2014a, 2014b) and Wolken (2013).

data gaps. Moreover, due to restrictions on the number of variables, it is very difficult to jointly model all the relevant risk transmission channels that are related to vulnerabilities in the residential real estate sector (encompassing aspects related to the valuation, household indebtedness and credit cycle). As a consequence, there might be a need for policy makers to complement model-based toolkits with broader model-free approaches.

Our work adds to the recent strand in the financial stability literature which highlights the benefits of simple approaches to systemic risk monitoring, especially as complements and cross-checks on signals derived from more complex approaches. Some authors argue that employing solely complex model-based monitoring approaches does not necessarily offer the best solution, in face of estimation uncertainty and an increasingly interconnected financial system. For instance, systemic risk assessments derived from complex models may still not reveal risks which could have been shown by simple metrics or rules of thumb (Danielsson and Zhou (2015)).[6] Therefore, in complex settings, both models and simple indicators can provide added value to risk monitoring processes. In particular, some simple indicators appear very useful, even if their joint power of predicting crises cannot be tested in the statistically robust way due to the limited number of crisis events. These indicators may offer additional information which may help to understand cross-country specifities of the developments in a given sector. They can also be used even if time series or cross-section information is not complete, as they do not depend on model parameters or coefficient estimates. More generally, the widespread use and power of heuristics has been documented in a number of studies in behavioural economics (e.g., Kahneman (2011), Gigerenzer and Brighton (2009), Haldane and Madouros (2012)).[7] The benefits of simple tools for policy purposes have also been highlighted by the International Monetary Fund (2011), while the value of simple approaches has been demonstrated for a number of financial stability problems.[8] The

[6] In general, some authors argued already long ago that under uncertainty, the distribution of risk simply cannot be known (Knight (1921)).

[7] For example, Aikman et al. (2015) show that simple 'fast and frugal' decision trees perform similarly to heavy econometric techniques in combining information.

[8] For example, Haldane and Madouros (2012) found that the explanatory power of simple equity to unweighted assets in predicting bank failure is found to be 10 times greater than the Basel Tier 1 Ratio. Other examples demonstrate that simple indicators often outperform complex ones in predicting

benefits of the model-free approach developed and tested in this paper include transparency of the framework and its components, easier interpretation of signals, reduced model uncertainty and avoiding threshold effects that typically characterize early warning models. The framework may therefore serve as a useful complement to more complex model-based approaches.

The model-free framework to monitor vulnerabilities related to the residential real estate sector introduced in this paper uses a selection of key indicators which account for three main dimensions of the real estate sector vulnerabilities. These include valuation (overvaluation, price-to-income and price-to-rent ratios), the resilience of the household sector (households debt service ratio, debt-to-income ratio, household leverage) and the credit cycle of the banking system (credit for house purchases to GDP, lending spreads, loan-to-deposit ratio). Covering all main dimensions of vulnerabilities related to residential real estate through a combination of indicators is important from the perspective of policy makers as it ensures a broad overview of this complex sector.[9] The choice of indicators is based on the variables used in the early warning literature on residential real estate vulnerabilities, combined with additional indicators highlighted by various policy bodies as being important monitoring metrics for this sector (for a more detailed discussion of the choice of indicators, see Section 2). The indicators from all three dimensions of vulnerabilities are standardised within a cross-country time-series panel, and aggregated into one vulnerability measure.

A significant feature of our framework, which is important from the policy perspective and has been so far to some extent missing in the literature, is a clear identification of vulnerabilities related to flows (indicating rising vulnerabilities) and stocks (indicating elevated vulnerabilities). Most early warning model-based approaches usually mix growth and level variables. However, analysing vulnerabilities based on a broad set of indicators along the stock and flow dimensions separately has value added from

banking crises (e.g., Haldane and Madouros (2012)) or identifying systemically important banks (e.g., Bengtsson, Holmberg, and Jönsson (2013)). Simple models also tend to perform better in modelling financial risks when samples are small (e.g., Haldane and Madouros (2012)).

[9]See also Himmelberg, Mayer, and Sinai (2005) for an example of an argument in favour of using broader sets of indicators in the policy context.

the policy perspective. For example, some macro-prudential policy instruments may be particularly effective in mitigating the build-up of risks, while other instruments may be better suited to deal with vulnerabilities related to high stocks, e.g., high stock of mortgage loans in the banking system. Another significant feature of our approach is the possibility of adding new variables when structural changes occur or when new data becomes available (for example, mortgage funding by non-bank intermediation).

The vulnerablity measure constructed within our framework is not based on model-calibrated variable selection which would claim to provide the best possible early warning system for residential real estate crises. Instead, it is based on equal weights of selected indicators. Still, our measure proves to be a significant predictor of historical real estate crises, with a forecasting performance similar to very advantageously in-sample calibrated model-based estimates. For example, a vulnerability map created by the measure as of end-2006 highlights most of the countries affected by residential real estate crises in the three subsequent years. In a broader quantitative comparison, our aggregated measure performs well, as compared to advantageously in-sample calibrated model-based estimate. In fact, out of all possible models with three-variable combinations, our measure is one of the top forecasting performers. It also beats some of the models that use larger sets of variables and proves to be robust to the definition of crisis periods. In view of some constraints of model-based estimates (e.g., the number of included factors given the scarcity of observed crises events and correlation structures), the model-free vulnerability measure is a useful complement of model-based tools for monitoring real estate vulnerabilities.

The remainder of the paper is outlined as follows. Section 2 describes the data and the methodology used to construct the monitoring framework. Section 3 assesses the early warning performance and robustness of our aggregate vulnerability measure. Section 4 concludes.

2 Data and methodology

Our framework proposes a simple approach to monitor vulnerabilities in residential real estate markets across countries and over time, covering three main dimensions: valuation, household indebtedness and credit cycle. The chosen indicators are intuitive, simple and publicly available, which adds to the transparency of the framework.[10] They are standardised, in order to offer a possibility of a cross-country reference, and aggregated into one composite vulnerability measure, for the cases when an overall summary is needed.

There are several benefits from adopting such a simple approach to monitoring vulnerabilities. Importantly, the measure does not depend on parameters of the model, the length of the data series or the number of crisis events (which are typically infrequent). Instead, the measure can accommodate a set of variables along the relevant vulnerability dimensions, including indicators with short time series if deemed relevant. In addition, missing values do not prevent the computation of the composite score. From a policy perspective, the results provide a cross-country vulnerability overview, which can be easily disaggregated into stock and flow dimensions, to focus in more detail on certain aspects of residential real estate vulnerabilities. Our approach enables the analysis to be framed in a consistent way across countries and regions, while at the same time providing an easy option to conduct a more specific analysis of stock and flows along vulnerability dimensions. Within each dimension, a comparison of indicators can be used to assess consistency among vulnerability signals.

This section presents data on indicators as well as methodology of their standardisation and aggregation. The data on crisis events is described in Section 3.2.

[10]See also Borio (2014) who recommends relying on simple and transparent indicators in policy contexts.

2.1 Selected indicators

The choice of indicators is based on the variables used in the early warning literature on residential real estate vulnerabilities, combined with additional indicators that have been highlighted by various policy bodies as important monitoring metrics for this sector. In particular, the framework uses a set of indicators covering the three key dimensions related to the real estate valuation, household indebtedness and the bank credit cycle. The indicators from all three dimensions of vulnerabilities are standardised within a cross-country time-series panel and aggregated to one vulnerability measure.

A detailed description of indicators, including data sources and related studies in the literature, is presented in Table 1. For the valuation dimension, we include overvaluation, the price-to-income and price-to-rent ratios. For this aspect of real estate vulnerabilities a set of papers has shown early warning abilities of various overvaluation metrics, including the price-to-income and price-to-rent ratios (see, e.g., Ferrari, Pirovano, and Cornacchia (2015), Himmelberg, Mayer, and Sinai (2005), Claessens, Kose, and Terrones (2008)). For the dimension related to the resilience of the household sector, we include households debt service ratios, the debt-to-income ratios and household leverage. Drehmann and Juselius (2012) show that households debt service ratio provides a very accurate early warning signal of systemic banking crises, while the level of the ratio is related to the size of the subsequent output losses. Also, higher debt in relation to income is shown to negatively affect future house prices (see, e.g., Gerdesmeier, Lenarčič, and Roffia (2012)). To complement the information from the indebtedness ratios, we also include household leverage to incorporate information on total assets.[11] For the dimension related to the credit cycle of the banking system, in order to capture information on the availability of mortgage funding as well as the importance of mortgage loans in the banking books, we use credit for house purchases to GDP, lending spreads and loan-to-deposit ratios. For example, Büyükkarabacaka and Valev (2010) demonstate that rapid household credit expansions generate vulnerabilities that often

[11]We include leverage to also take financial assets of households into account.

Indicators	Description	Data source	Rationale
Valuation			
Price- to-income (PTI)	Nominal house prices/nominal gross disposable income (Index 2010=100).	OECD.	Highlighted by OECD –Focus on housing, ESRB 2016. Strong indicator of forthcoming crises (Barrell et al. 2010; Borio & Drehmann 2009; Drehmann et al. 2010; Claessens et al. 2011; Mendoza & Terrones 2008; Riiser 2005).
Price- to-rent (PTR)	Nominal house prices/nominal rent (Index 2010=100).	OECD.	Highlighted by OECD – Focus on housing, IMF – Global Housing Watch, ESRB 2016. Significant indicator of forthcoming crises (Barrell et al. 2010; Borio & Drehmann 2009; Drehmann et al. 2010; Claessens et al. 2012; Mendoza & Terrones 2008; Riiser 2005; Himmelsberger 2005).
Estimates of the over/undervaluation of residential property prices in selected EU countries (Overval)	ECB 2015 computation, % deviation of actual house prices from model-based equilibrium (for methodological details, see ECB 2015).	Eurostat, national sources, ECB and ECB calculations, published in ESRB risk dashboard.	
Household indebtedness			
Households debt to disposable income (DTI)	Ratio of household debt to the annual moving sum of household gross disposable income.	MUFA and NFA Eurostat ESA 2010, published in the ESRB risk dashboard.	Highlighted by ESRB 2016. Gerdesmeier et al. (2012)
Debt service ratio - Households (DSR)	Ratio of interest payments plus amortisations to income.	BIS.	Highlighted by ESRB 2016; indictor of forthcoming crisis (Drehmann & Juselius 2012).
Households debt to total financial assets (HH Lev)	Ratio of household debt to household total financial assets.	IEAQ - Quarterly Euro Area Accounts.	Similar as debt to disposable income ratio (DTI) but also takes into account the asset side of household balance sheet (wealth of households relative to debt level).
Credit cycle			
Credit for house purchases (CreditHP_GDP)	Level: MFIs credit to domestic households for house purchase to GDP (monthly data). 1y change: year on year growth of credit for house purchase (monthly data).	ECB Balance Sheet Items, European National Accounts and authors' calculations.	Highlighted by ESRB 2016; Büyükkarabacak & Valev 2010.
Lending spreads (lendingspreads)	Difference between lending rates for house purchases and money market rates.	ECB MFI Interest Rate Statistics, Bloomberg and authors' calculations.	Indicating banks' pricing of loans, as compared to the cost of money market funding.
Loan-to-deposit (loan_deposit)	Ratio of bank total loans to total deposits vis-à-vis the domestic and euro area households, NFCs and non-MFI residents excluding the general government.	ECB, published in ESRB Risk Dashboard.	Highlighted by Drehmann & Juselius 2012, as well as in several publications of the Bank for International Settlements.

Table 1: Overview of indicators related to residential real estate vulnerabilities

NOTE: The table presents an overview of indicators used in the analysis, including their description, data source and references to the literature.

precede crises. Beyond this data, for robustness purposes, we also consider several other indicators and check their empirical performance (see Annex C).

The sample covers all EU countries in the period from Q1-2000 to Q2-2015.[12] For most countries in the sample, the data is available for all or almost all indicators.[13] The sample period and the coverage of crisis events is broadly comparable to some other recent studies on the subject, e.g. to Ferrari, Pirovano, and Cornacchia (2015). For the details of crisis events covered by the sample, see Annex B.

2.2 Determining the vulnerability scores

The composite vulnerability measures are calculated in two steps. Step 1 determines vulnerability levels and changes for each main indicator and each country in the sample. It involves a standardisation, in order to offer a possibility of a cross-country reference. Step 2 aggregates the indicators to one composite 'vulnerability score', which is useful for the cases when an overall summary is needed. Such a stepwise methodology facilitates the tractability of the measure in practice and enables an easy decomposition if needed in the policy context.

The vulnerability assessment for each indicator (step 1) is based on percentiles of pooled panel data from all analysed countries (see, e.g., Crocker and Algina (1986)). Each country i is attributed in each period t with a 'level score' and a 'flow score' for each indicator k, ranging from 0 to 1 (1 being the highest historical value in the panel sample), defined as their percentile rank in the distribution as follows:

$$L_{k,i,t} = \frac{\sum_{j,\tau} I(l_{k,j,\tau} \leq l_{k,i,t})}{\sum_{t,\tau} L_{k,j,\tau}} * 100\%, \tag{1}$$

and

$$C_{k,i,t} = \frac{\sum_{j,\tau} I(c_{k,j,\tau} \leq c_{k,i,t})}{\sum_{t,\tau} C_{k,j,\tau}} * 100\%, \tag{2}$$

[12] For illustrative purposes, the sample takes into account data for all EU countries. The framework can be applied to any selected set of countries or regions at any selected time period.

[13] In particular, the data is available for all indicators throughout most of the period for 11 out of 28 EU countries. 6 countries have one missing indicator, 5 countries have two missing indicators, 2 countries have three missing indicators and 4 countries have four missing indicators.

where $L_{k,i,t}$ and $C_{k,i,t}$ denote the percentile ranks of the level and the change of an indicator k for a country i at time t, according to the percentile in the full historical distribution of the indicator. $l_{k,i,t}$ and $c_{k,i,t}$ denote the value and the quarterly change of the indicator k for a country i at time t. Figure 1 shows an example for a full distribution of one of the indicators in the dimension of household indebtedness vulnerabilities: the household debt to total financial assets ratio. The dots mark the position of EU countries within the historical distribution as of end-2006. The percentile rank of the level of the indicator for country i at time t ($L_{k,i,t}$) can be interpreted as the area under the curve to the left of a given point, e.g., marked for Finland in Figure 1. The rank shows that, for this particular example, the level of the related vulnerability is relatively high from the historical and cross-country perspective, as ca. 75% of the data in the panel recorded lower household debt than the one in the illustrated country at the end-2006. The same interpretation can be applied to the percentile rank of the one-period change of the indicator ($C_{k,i,t}$). As shown in Figure 1, the percentile rank only depends on the cross-country and time-series distribution and is not related to any economically motivated thresholds or the probability of crisis events. The figure also suggests that the informativeness of our measure is better if the chosen set of countries is relatively large and the time series are long. Overall, the interpretation of the developments of our measure from the policy perspective should be accompanied by the analysis of structural differences among countries and over time.

Computing composite vulnerability scores (step 2) for countries' vulnerability levels and flows is based on the percentile ranks $L_{i,t}$ and $C_{i,t}$ calculated in the previous step. A 'composite level score' and a 'composite flow score' are determined for each country and each date and computed as a non-weighted average of the scores in each indicator at that date:

$$L_{i,t} = 1/k \sum_{k} L_{k,i,t}, C_{i,t} = 1/k \sum_{k} C_{k,i,t} \tag{3}$$

An example of an overview of the aggregate score in the levels (y-axis) and developments (x-axes) as of end-2006, i.e., several quarters before the onset of real estate crises in many countries, is presented in Figure 2. The countries which experienced subsequent crises in the residential real estate markets are marked in the figure with red dots. This simple overview indicates that most of the countries flagged as having high vulnerability levels, according to the simple aggregated measure, indeed experienced residential real estate crises in the quarters that followed. Moreover, some countries with vulnerabilities flagged as rising very fast also experienced subsequent real estate-related crises. Framing the analysis of vulnerabilities along both dimensions, i.e. levels and dynamics, as shown in Figure 2, might be particularly useful for the policy makers, e.g., in view of the fact that many policy tools are best suited to address the dynamics of the vulnerabilities.[14]

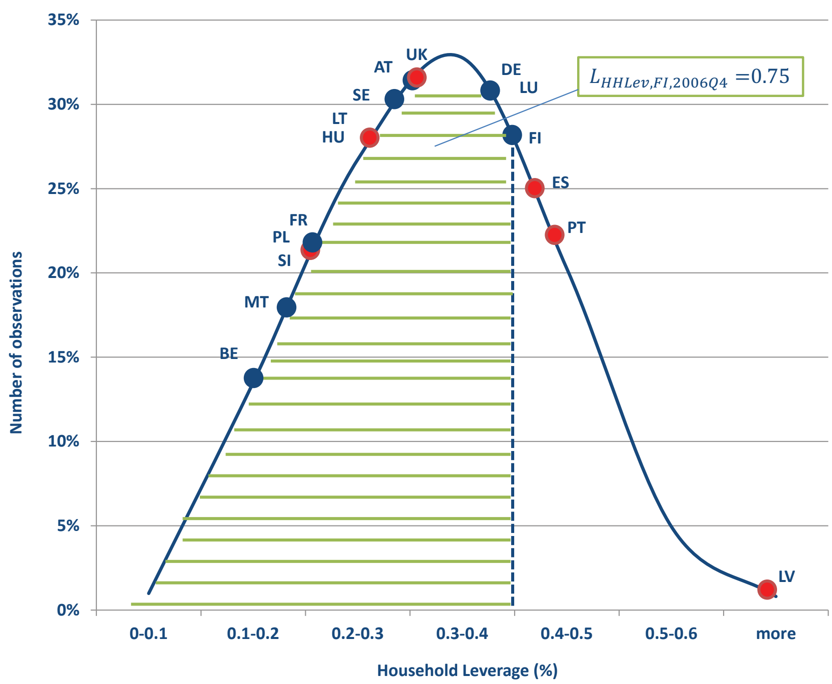

Figure 1: Example of historical panel distribution for one of the indicators and calculation of the percentile rank

NOTE: Authors' calculations, as based on data listed in Table 1. The figure shows an example of a distribution of household debt to total financial assets ratio (HH_lev) as of end-2015. X-axis denotes the buckets of the values of HH_lev, as observed historically across all countries. Y-axis denotes the frequency of observations in percentages of all observations. Total number of quarterly observations: 1111. Points indicate the position of countries as of end-2006. The percentile rank for a given country at a given date can be interpreted as percentage of the area under the curve. The area marks an example for $L_{HHLev,FI,2006Q4}$.

[14] Another advantage of the flow indicator, as opposed to just taking the changes of the level indicator, is that it offers a decomposed information on the dynamics of each subcomponent separately.

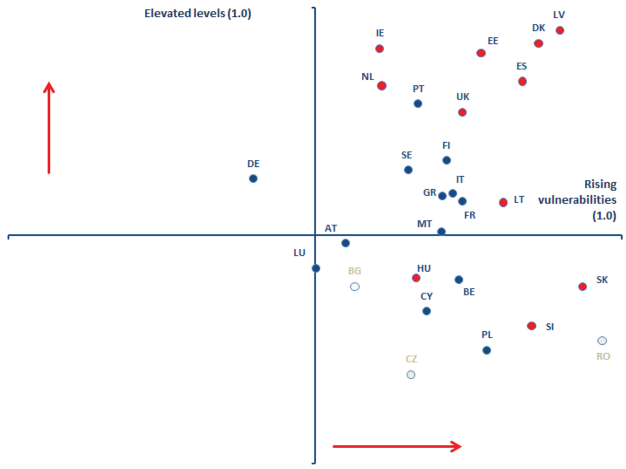

Figure 2: End-2006 map of composite vulnerability scores for levels (y-axis) and changes (x-axis)

Note: Authors' calculations, as based on data listed in Table 1. The Y axis denotes the level of vulnerability for the composite score. The x-axis denotes the change in the level over the previous year. Red dots denote countries that experienced a real estate crisis several quarters after end-2006 (see also Annex B for comparison). Colouring of the chart is for illustrative purposes only and is not based on any assumed thresholds. Scores for BG, CZ, RO (marked grey) are not considered comprehensive enough for analysis due to missing indicators in 2006. MT and PL also have some missing indicators, which should warrant some caution when interpreting the results.

For policy-related monitoring purposes, benefits of clear presentation and easily interpretable information are crucial.[15] Various data visualization techniques have been more extensively employed in recent years in the policy context, in particular in relation to the complex financial systems or economic interdependencies. Our framework enables an easy illustration of the scope and changes of vulnerabilities in the aspects of residential real estate valuation, household indebtedness and the credit cycle. For illustrative purposes, Figures 3 and 4 present a possibility of a disaggregated analysis of signals from the set of indicators for two selected countries (Ireland and the Netherlands) at two selected points in time (end-2006 and end-2014).[16] For both examples, the charts at the end of 2006 indeed clearly highlight the very high level of vulnerabilities in Ireland

[15]See Aikman et al. (2015) for a discussion. As Schwabish (2014) puts it, "an effective graph should tap into the brain's 'pre-attentive visual processing'", which allows for the perception of multiple basic visual elements simultaneously. Ware (2013) further adds that "We can easily see patterns presented in certain ways, but if they are presented in other ways, they become invisible.... If we can understand how perception works, our knowledge can be translated into rules for displaying information. Following perception-based rules, we can present our data in such a way that the important and informative patterns stand out. If we disobey the rules, our data will be incomprehensible or misleading".

[16]See Annex B for detailed starting and end dates of crises in these countries.

and to a lesser extent in the Netherlands, across most of our risk indicators, grouped along key vulnerability dimensions. Several years after the bust, i.e. at end-2014, the vulnerabilities had reduced significantly. In Ireland the banks had reduced their lending exposures, overvaluation in the housing sector has disappeared across the different indicators, and vulnerabilities from lending spreads receded. However, we can also observe that vulnerabilities remained in certain dimensions, as the household sector had not yet managed to deleverage, and was still significantly indebted at end-2014. Such a disaggregated analysis may be useful for policy makers since the choice of macroprudential instruments can be related to the nature of the vulnerability (e.g., vulnerabilities related to the banking or household sector). Moreover, the framework allows for a quick consistency analysis of signals from several indicators within one vulnerability dimension and accounts for changes in the data availability over time.

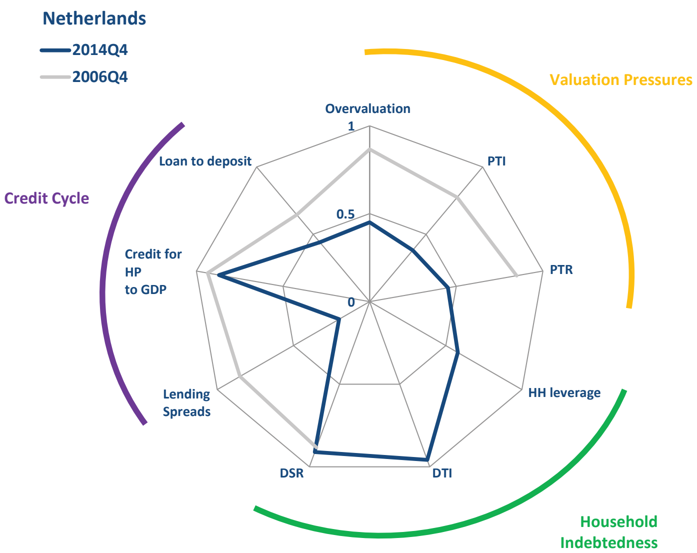

Figure 3: Overview of vulnerability measure across dimensions, indicators and over time - example of the Netherlands (end-2006 and end-2014)

NOTE: Authors' calculations, as based on data listed in Table 1. Illustration of indicators across three main dimensions of vulnerabilities related to the residential real estate: valuation, household indebtedness and credit cycle. Data as of end-2006 and end-2014 for illustrative purposes.

Another useful possibility to monitor the developments of the vulnerabilities is to track the aggregate vulnerability measure over time, possibly along with some crisis-related in-

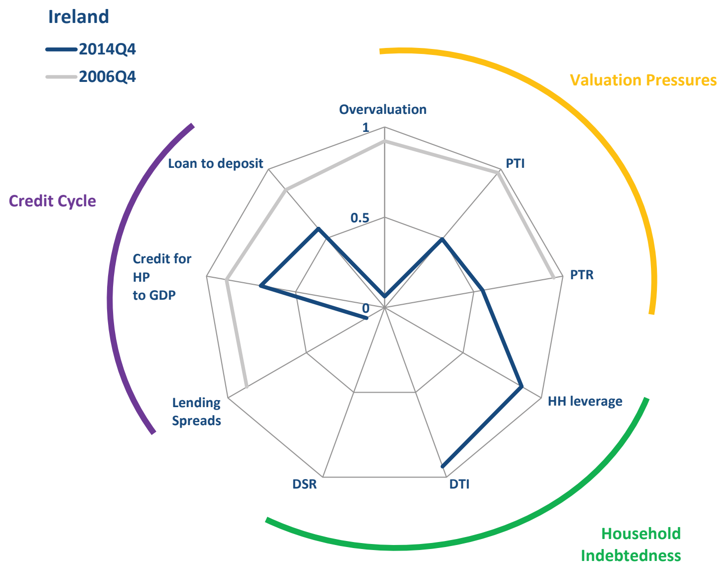

Figure 4: Overview of vulnerability measure across dimensions, indicators and over time - example of Ireland (end-2006 and end-2014)

NOTE: Authors' calculations, as based on data listed in Table 1. Illustration of indicators across three main dimensions of vulnerabilities related to the residential real estate: valuation, household indebtedness and credit cycle. Data as of end-2006 and end-2014 for illustrative purposes.

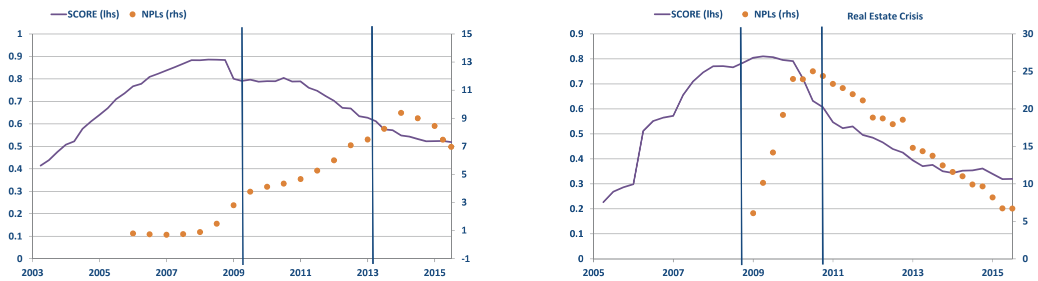

Figure 5: Time series of the aggregate vulnerability score over time and non-performing loans resulting from the 2008/2009 real estate crisis - examples of Spain (left panel) and Lithuania (right panel)

NOTE: IMF for NPL data and authors' calculations, as based on data listed in Table 1. The first vertical line denotes the beginning of the real estate crisis, the second line denotes the end, according to the Ferrari, Pirovano, and Cornacchia (2015) crisis dates.

dicators, which signal materialisations of real estate vulnerabilities, e.g. non-performing loans.[17] Using the selected 2009 housing crises in Lithuania and Spain as illustrative examples, Figure 5 shows the level and dynamics of the aggregate vulnerability measure in the real estate markets of those countries in the pre-crisis and crisis phases. The vulnerability scores increase before the crisis. After the crisis starts around the peak of our vulnerability score, the latter declines as vulnerabilities unwind in some or all key dimensions. In addition, a comparison to the dynamics of non-performing loans shows that these are clearly rising with a lag, once the risks have actually materialized.[18] The charts also point to the usefulness of the distinction between the 'level' and 'flow' aspects captured by the monitoring framework, in particular for countries with very fast run-ups to high levels, which can be best captured in an explicit panel comparison of the vulnerability dynamics (see, e.g., Figures 2 and 5 for the case of Lithuania). Results for all EU countries are available upon request.

These examples illustrate that our framework provides some insights on real estate-related vulnerabilities by showing the evolution of vulnerabilities both over time and across countries (see Figures 2 and 5). Moreover, it is possible to analyse vulnerabilities along several dimensions for selected countries and selected dates, taking into account levels and the dynamics, as well as cross-check the consistency of signals received from different indicators (see Figures 3 and 4).[19] Finally, the figures provide some preliminary indications of the predictive power of the framework by correctly identifying the build-up of risk in countries that later experienced real estate crises.

[17]Due to data shortcomings, the data on NPLs cover all loan exposures (residential real estate exposures and other loan exposures).

[18]This supports the interpretation of non-performing loans as an indicator of the consequences of a real estate bust, rather than an early warning indicator. For this reason, non-performing loan data is not part of our monitoring framework, but is instead used to validate the signals resulting from our monitoring approach.

[19]See Aikman et al. (2015) and Lepers and Sanchez-Serrano (2017) for a discussion of the insights from a "narrative" approach to the understanding of the origins of risk, as well as the benefits of disaggregating indices by intuitive 'poles' of vulnerabilities. These papers take a broader perspective on financial stability, rather than focus on the real estate sector.

3 Assessing early warning performance and robustness

This section presents an assessment of the early warning performance of the vulnerability monitoring framework outlined in Section 2. For this purpose, we focus on aggregate vulnerability levels, since they can be directly compared to the results from model-based approaches used in the literature. The predictive power of the aggregate vulnerability measure is compared to the predictive power of models constructed on the basis of the indicators included in the aggregate vulnerability measure, as well as to one selected model from the recent literature.

The calibration of our vulnerability measure is a priori (equal weighting of nine indicators) and, therefore, its performance can be interpreted as an out of sample performance. In contrast, for the model-based measures, one needs to calibrate the weights among sub-indicators by estimating the model. In our exercise, we calibrate the models in an advantageous way, i.e. the coefficients are calibrated based on in-sample estimates, which eliminates any forecasting uncertainty to the advantage of the model-based calibration. Consequently, our results are biased in favour of model-based approaches, and still the model-free measure performs very well in comparison to the distribution of model performance.

3.1 Empirical test of framework's predictive power: set-up

First, the predictive power of the indicators included in the monitoring framework is checked using a set of uni- and multivariate logit models. We show that all indicators constituting our aggregated measure are significant and their coefficients are stable for various specifications.[20]

Second, the predictive power of the aggregate vulnerability measure is compared to the predictive power of models constructed on the basis of the indicators included in the aggregate vulnerability measure, as well as to one selected model from the recent

[20] We can't test all indicators simultaneously in one large model as they are correlated (see Table 2).

literature (Ferrari, Pirovano, and Cornacchia (2015)). The empirical test of the vulnerability monitoring framework is based on the standard approach of early warning indicator signalling (see Annex A for a short review). Using two different sets of crises dates (see Annex B and Section 3.2 for the details on the crisis data), the indicators are tested, based on a prediction horizon of 12 quarters prior to the onset of residential real estate crises. Importantly, all models are estimated on very advantageous terms, assuming no uncertainty about the data, i.e., by taking the full set of historical observations for the estimation of model parameters. In this way, we assure the best possible fit of all estimated models and minimise the estimation uncertainty due to the small sample problems. To assure the best possible data availability, we take two approaches in our tests: using a non-balanced sample (including all data available for each specification) and a balanced sample (restricting all specifications to one common data sample). The non-balanced samples maximise the number of data, including crisis events and pre-crisis observations, but are not directly comparable. The balanced samples ensure the precise comparability by restricting the data to one common, but loose in this way crisis observations. We take both approaches to check the performance of our model-free measure in a comprehensive way.

We test the forecasting performance of all possible three-variable combinations. Furthermore, we test several feasible four-variable model combinations, with the restriction that there must be at least one variable related to each of the real estate vulnerability dimensions. Higher number of variables is not feasible in view of the small number of crisis events (see Annex B) and would lead to overfitting and multicollinearity problems. Based on the results of all sets of models, a 'basic model' is chosen which has the highest number of non-correlated significant variables, but the number of parameters still allows reliable estimates given data restriction associated with an early warning set-up.[21] The basic model is chosen for illustrative purposes to provide an example of a model-based framework which would result from a model-based selection among the indicators used

[21] Alternatively, one could use Bayesian model averaging. We choose to test all possible model combinations to illustrate the distribution of all results, including also the top-performing models, which would be largely reflected in the model average.

in our proposed monitoring framework. The predictive power of the 'basic model' is also compared to an example of a model used in Ferrari, Pirovano, and Cornacchia (2015).

Having calibrated the 'basic model' on our data, assuring the best possible fit on the full ex-post dataset, we compare the predictive performance of the models to the performance of the simple aggregate vulnerability score (as introduced in Section 2). The measure proves to be a significant predictor of historical real estate crises, with the forecasting performance better than the majority of advantageously in-sample calibrated model-based estimates. Importantly, its performance is also quite stable across two differently defined databases of crisis periods. In view of significant advantages of the simple vulnerability score and constraints of model-based approaches, the good forecasting performance of the model-free vulnerability measure illustrates that our framework is a potentially important monitoring tool which may complement model-based toolkits for analysing vulnerabilities in the residential real estate sector.

3.2 Defining crises periods

For robustness purposes, two alternative definitions of real estate crises are used (see Annex B for the details of both crisis datasets): first, a quantitative crisis dataset based on definition of housing bust periods; and second, a qualitative crisis dataset used in Ferrari, Pirovano, and Cornacchia (2015).[22]

In the quantitative crisis dataset, a housing bust is defined using a simple computation similar to the one used in International Monetary Fund (2009) and based on the Bordo and Jeanne (2002) definition: busts are periods when the four-quarter moving average of the growth rate of real house prices is below a threshold, which equals the average growth rate of the whole sample minus one standard deviation of the growth rates in the whole sample.[23] The duration of a bust is the period for which the four-quarter

[22] The database used in Ferrari et al (2015) is the outcome of a qualitative compilation by the 28 EU Member States in the ESRB Advisory Technical Committee, building on the ESCB Heads of Research (HoR) Group's banking crises database, and adjusted by ESRB ATC members' judgment to reflect only crises stemming from real estate.

[23] There are several ways to define housing booms and busts: Bordo and Jeanne (2002) define a bust as a period when the three-year moving average of the growth rate of asset prices is smaller than the average growth rate minus 1.3 times the standard deviation of growth rates.

moving average of the growth rate of house price remains below the relevant threshold. Because periods $t-3$ to t are labelled as a bust, there is a minimum duration of one year for all busts.

$$\frac{g_{t-3} + g_{t-2} + g_{t-1} + g_t}{4} < \overline{g} - \sigma(g) \tag{4}$$

This method is objective, straightforward and seems intuitively efficient in identifying some well-known housing busts including the Finnish crisis of the 90's, or the Spanish, Irish and Lithuanian busts after 2008. However, it does not signal a crisis in Sweden in 2008 but points to real estate problems in Greece and Portugal during the recent sovereign debt crisis.

In the subsequent analysis, pre-crisis periods are defined as 12 quarters prior to a crisis, whereas the crisis periods themselves are dropped from the sample. We report the results based on the quantitative crisis dataset in Section 3.3 and make a robustness check for the qualitative crisis dataset (presented in Annex C).

3.3 Empirical assessment of the predictive power of the monitoring framework in comparison to model-based approaches

Consistent with the early warning literature, we use a simple multivariate logit model, regressing a pre-crisis dummy on early warning indicators:

$$Pr(y_{i,t} = 1|\alpha_i, X_{K,i,t}) = F(\alpha_i + X'_{K,i,t}\beta_K), \tag{5}$$

where $y_{i,t}$ represents a pre-crisis dummy variable, the matrix $X_{K,i,t}$ compiles all indicators and a constant, and the vector β_K denotes the corresponding regression coefficients.

Table 2 reports the correlation and autocorrelation of the variables. Not surprisingly, some indicators are significantly correlated: price-to-rent (PTR) and price-to-income (PTI) have the same numerator, overvaluation is calculated relative to house prices, debt service ratio (DSR) and debt-to-income ratio (DTI) have the same denominator, while debt-to-income (DTI) and household leverage (HHLev) are both related to the household indebtedness. As discussed in Section 2, all these indicators are important in describing different dimensions of real estate-related vulnerabilities, and also enable a consistency check within each of the vulnerability dimension. For modelling purposes, however, high correlations between some of the variables prevent the possibility of including all coefficients into a model, since such specification would result in multicollinearity and spurious results. Therefore, a calibration of a model which would give the best forecast performance results, include a wide set of indicators, avoid multicollinearity and account for a small sample problems needs to be based on a set of partial regressions and a comparison of parameter stability across various specifications.

	PTI	PTR	overval	DSR	DTI	HHlev	creditHP _GDP	lending spreads	loan_ deposit
PTI	1.00								
PTR	0.94	1.00							
overval	0.50	0.48	1.00						
DSR	0.28	0.25	0.20	1.00					
DTI	0.21	0.18	0.14	0.96	1.00				
HHlev	0.38	0.38	0.12	0.48	0.50	1.00			
creditHP_GDP	0.30	0.29	0.14	0.82	0.87	0.59	1.00		
lendingspreads	-0.04	-0.06	0.00	0.20	0.22	-0.12	0.21	1.00	
loan_deposit	0.19	0.17	0.09	0.45	0.54	0.59	0.62	-0.23	1.00
Autocorrelation	0.98	0.99	0.96	1.00	1.00	0.99	1.00	0.93	0.99

Table 2: Correlation among the indicators included in the monitoring framework
NOTE: The table presents correlation coefficients among the indicators included in the monitoring framework, with the autocorrelation coefficients shown in the last row.

We estimate and statistically evaluate early warning performance of logistic models for a set of uni- and multivariate combinations of the indicators of our monitoring framework and compare the performance of the aggregate level score from our monitoring framework against the model performance. Importantly, to the advantage of model-based estimates in comparison to our model-free measure, the calibration is made in the most favourable way possible, assuring the best possible fit by the estimation on a full ex-post dataset. We test the predictive power of various combinations of the variables in our framework, taking into account all tri-variable combinations and some feasible four-variable models. Finally, the performance of the optimally weighted framework is then compared with the performance of our 'level' score and the performance of the best logit model of Ferrari, Pirovano, and Cornacchia (2015) using identical sample of observations.

VARIABLES	(1) Logit coeff	(2) Logit coeff	(3) Logit coeff	(4) Logit coeff	(5) Logit coeff	(6) Logit coeff	(7) Logit coeff	(8) Logit coeff	(9) Logit coeff
PTI_L1	0.102*** (0.00820)								
PTR_L1		0.0709*** (0.00819)							
overval_L1			0.0508*** (0.00687)						
DSR_L1				0.215*** (0.0224)					
DTI_L1					0.00642** (0.00251)				
HHlev_L1						3.422*** (1.015)			
creditHP_GDP_L1							1.434*** (0.402)		
lendingspreads_L1								-0.390*** (0.0812)	
loan_deposit_L1									0.00772*** (0.00133)
Constant	-12.29*** (0.862)	-8.976*** (0.857)	-2.069*** (0.0942)	-4.473*** (0.301)	-2.676*** (0.295)	-3.142*** (0.371)	-2.528*** (0.177)	-1.076*** (0.171)	-3.067*** (0.206)
Observations	994	940	1,359	629	675	932	1,280	1,155	1,285
Pseudo R2	0.2533	0.1484	0.0638	0.1496	0.0141	0.0180	0.0159	0.0366	0.0275
AUROC	0.8282	0.7699	0.6810	0.8322	0.5999	0.5919	0.5693	0.6625	0.6562
Type I Error #	12.00%	10.95%	21.35%	30.43%	31.65%	23.21%	38.67%	13.66%	22.00%
Type II Error #	41.47%	54.30%	55.55%	22.86%	70.47%	65.12%	58.85%	73.44%	57.62%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
# Type I and Type II Errors are calculated for informative purposes for a cutoff of 0.1 (signal issued if the model gives Pr(Y=1)>0.1)
Type I Error is the fraction of missed crises; Type II Error is the fraction of false alarms

Table 3: Results of univariate regressions - quantitative crises dataset
NOTE: The table presents the coefficients of univariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

The results of the univariate regressions are shown in Table 3. Disregarding the omitted variable problems, a comparison of the predictive power of the individual variables (AUROC), gives an initial idea of the best performing indicators within a more complex model. Table 4 shows the results of the test of the predictive power of various combinations of the indicators, as well as an example of a 'basic model' chosen from the possible combinations of the regressors (column 1). The samples are chosen so that to maximise the number of observations for each set of variables.[24] We also compare the model performance for a sample restricted to the same number of observations later in this section. Reflecting a very advantageous estimation on an in-sample basis, the AUROC are relatively high and the Type I and Type II errors are relatively low. The various combinations of variables illustrate that, even for different sample sizes, most of the indicators are significant with rather stable coefficients across specifications, which means that all of them are suitable for inclusion in broad-based monitoring tools and contain information on different dimensions of real estate-related vulnerabilities, which is valuable in an early warning framework. The 'basic model' thus drops variables that are highly correlated with some others and needs to stay limited to a subset of variables.

The regression results used to define an optimal weighting for each indicators, i.e. the 'basic model', can be now compared with other models and the simple monitoring framework, in terms of their performance in signalling vulnerabilities in the real estate sector. Restricting the sample to an identical sample of observations, without which a strict comparison of AUROC would not be possible (Cleves (2002)), we compare the performance of the 'basic model' with the performance of the model-free measure (see also discussion in Section 3.1 on the trade-off between choosing non-balanced and balanced samples). Since all models are calibrated on the in-sample basis, they all perform very well in terms of early warning properties. Still, Table 5 and Figures 6-7 show that our measure performs better than most of in-sample model-based calibrations. In particular, the model-free measure is in the top 10 percentile of feasible model-based combinations of underlying indicators. To further compare our model-free measure, as well as the 'ba-

[24] In this case, pre-crisis observations range from 51 (specification 1, 5 crisis events) to 132 (specification 7, 11 crisis events). For comparison, pre-crisis observations in Table 3 range from 69 (specification 4, 6 crisis events) to 178 (specification 3, 17 crisis events). For the restricted, balanced samples, which ensure strict comparability of models (see also discussion in Section 3.1 on the trade-off between choosing non-balanced and balanced samples), pre-crisis observations in Table 5 amount to 39 (4 crisis events) and in Table 6 to 49 (3 crisis events). The last sample is chosen in order to be comparable to the sample in Ferrari, Pirovano, and Cornacchia (2015).

VARIABLES	(1) **Basic Model**	(2)	(3)	(4) **Examples: 4-variable models**	(5)	(6)	(7) **Examples: 3-var models**	(8)
PTI_L1	0.0955***					0.0785***		
	(0.0164)					(0.00931)		
PTR_L1		0.0848***						0.0740***
		(0.0107)						(0.0117)
overval_L1	0.0263		0.0637***	0.0708***	0.0510***		0.0519***	
	(0.0269)		(0.0111)	(0.0155)	(0.0100)		(0.00965)	
DSR_L1	0.571***			0.175***				
	(0.0726)			(0.0616)				
HHlev_L1	17.60***	3.877**	4.462***		0.439	4.254***	1.403	
	(3.376)	(1.581)	(1.269)		(1.253)	(1.363)	(1.227)	
DTI_L1		0.0126***	0.00701**					0.0133***
		(0.00423)	(0.00321)					(0.00388)
lendingspreads_L1	-1.641***	-0.445***	-0.430***	-0.503***	-0.256**	-0.233		-0.500***
	(0.252)	(0.137)	(0.110)	(0.134)	(0.106)	(0.147)		(0.117)
creditHP_GDP_L1				1.500		0.0671		
				(1.148)		(1.071)		
loan_deposit_L1					0.00723***		0.00456***	
					(0.00206)		(0.00152)	
Constant	-22.19***	-12.44***	-3.651***	-4.108***	-2.579***	-11.06***	-3.244***	-9.773***
	(2.803)	(1.455)	(0.602)	(0.435)	(0.544)	(1.089)	(0.451)	(1.432)
Observations	440	543	578	560	736	623	879	549
Pseudo R2	0.5197	0.2213	0.1723	0.2927	0.1028	0.1791	0.0761	0.1742
AUROC	0.9515	0.8180	0.7612	0.8672	0.7256	0.7905	0.6946	0.7837
Type I Error [#]	3.92%	22.73%	32.86%	18.84%	14.29%	18.29%	26.00%	21.13%
Type II Error [#]	15.94%	35.01%	35.24%	23.63%	49.84%	41.59%	46.98%	43.51%

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Type I and Type II Errors are calculated for informative purposes for a cutoff of 0.1 (signal issued if the model gives Pr(Y=1)>0.1)
Type I Error is the fraction of missed crises; Type II Error is the fraction of false alarms

Table 4: Results of multivariate regressions - quantitative crises dataset

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

sic model', to the best logit model in Ferrari, Pirovano, and Cornacchia (2015), we need to restrict the database to cover exactly the same period as the data in the reference paper. The simple monitoring framework, as here represented by the aggregate vulnerability score in the level dimension, performs very close to the in-sample fitted models (see Table 6). Given the significant advantages of the simple vulnerability score, as described in Sections 1 and 2, these results show that, overall, the monitoring framework using simple aggregated vulnerability scores is a very useful complement to model-based approaches for analysing vulnerabilities in the residential real estate sector.

As a robustness check, we calibrate the exercise to the qualitative crisis dataset (see Section 3.2) for the same set of countries, variables and the same horizon of predictions. The results show that the aggregate measure again performs very well in comparison to model-based in-sample calibrated indicator estimates (Annex C).

	Obs	ROC Area	Std. Err.	-Asymptotic Normal-- [95% Conf. Interval]			Obs	ROC Area	Std. Err.	-Asymptotic Normal-- [95% Conf. Interval]	
allhp24	341	0.9688	0.0086	0.95202	0.98566	allhp12	341	0.9211	0.0154	0.89097	0.95127
Basic_Model	**341**	**0.9609**	**0.0096**	**0.94201**	**0.97971**	allhp26	341	0.9194	0.0148	0.89039	0.94846
allhp34	341	0.9585	0.0108	0.93736	0.97961	allhp51	341	0.9109	0.0162	0.87915	0.94255
allhp31	341	0.954	0.0109	0.93264	0.97532	allhp1	341	0.9044	0.0188	0.86747	0.94133
allhp33	341	0.9516	0.0113	0.92938	0.97383	allhp2	341	0.9021	0.018	0.86688	0.93734
Level_score	**341**	**0.9513**	**0.0111**	**0.92967**	**0.97303**	allhp3	341	0.9016	0.0181	0.86611	0.93709
allhp32	341	0.9513	0.0116	0.92850	0.97403	allhp4	341	0.9015	0.0194	0.86350	0.93952
allhp36	341	0.9508	0.0116	0.92807	0.97361	allhp53	341	0.9011	0.0173	0.86712	0.93506
allhp6	341	0.949	0.0114	0.92670	0.97125	allhp8	341	0.8999	0.0168	0.86692	0.93288
allhp35	341	0.9471	0.0126	0.92234	0.97187	allhp52	341	0.8971	0.0186	0.86063	0.93356
allhp30	341	0.9414	0.0123	0.91722	0.96562	allhp50	341	0.8964	0.018	0.86110	0.93174
allhp14	341	0.9387	0.0135	0.91218	0.96522	allhp54	341	0.8962	0.0181	0.86074	0.93175
allhp15	341	0.9382	0.013	0.91266	0.96372	allhp42	341	0.8957	0.0193	0.85776	0.93354
allhp13	341	0.9381	0.0133	0.91198	0.96423	allhp49	341	0.8946	0.0181	0.85924	0.93002
allhp16	341	0.9371	0.0137	0.91033	0.96384	allhp41	341	0.8933	0.0178	0.85839	0.92816
allhp19	341	0.9349	0.0143	0.90678	0.96298	allhp9	341	0.8894	0.0189	0.85228	0.92646
allhp18	341	0.9343	0.0139	0.90700	0.96157	allhp10	341	0.8874	0.02	0.84830	0.92653
allhp23	341	0.9342	0.0143	0.90621	0.96219	allhp7	341	0.8841	0.02	0.84499	0.92322
allhp17	341	0.9328	0.0146	0.90418	0.96150	allhp47	341	0.8772	0.0189	0.84016	0.91430
allhp20	341	0.9326	0.0144	0.90445	0.96072	allhp37	341	0.8452	0.0255	0.79524	0.89520
allhp29	341	0.9299	0.0139	0.90265	0.95709	allhp48	341	0.8411	0.0248	0.79250	0.88979
allhp21	341	0.9294	0.0152	0.89971	0.95918	allhp38	341	0.8249	0.0319	0.76247	0.88739
allhp22	341	0.9272	0.0158	0.89624	0.95806	allhp44	341	0.8141	0.0295	0.75617	0.87195
allhp5	341	0.9259	0.0148	0.89694	0.95482	allhp43	341	0.8099	0.0316	0.74806	0.87174
allhp28	341	0.9255	0.0148	0.89636	0.95454	allhp40	341	0.8094	0.0338	0.74309	0.87570
allhp27	341	0.9247	0.0149	0.89549	0.95389	allhp39	341	0.7918	0.039	0.71540	0.86823
allhp25	341	0.9227	0.0154	0.89255	0.95292	allhp46	341	0.7179	0.0476	0.62463	0.81110
allhp11	341	0.9218	0.0145	0.89343	0.95017	allhp45	341	0.7168	0.0474	0.62386	0.80983

Table 5: Comparison between the monitoring framework and model-based approaches - quantitative crises dataset

NOTE: The table presents the comparison of ROC values of all 3-variable model combinations, with the lines of "basic model" and "level score" highlighted for comparison.

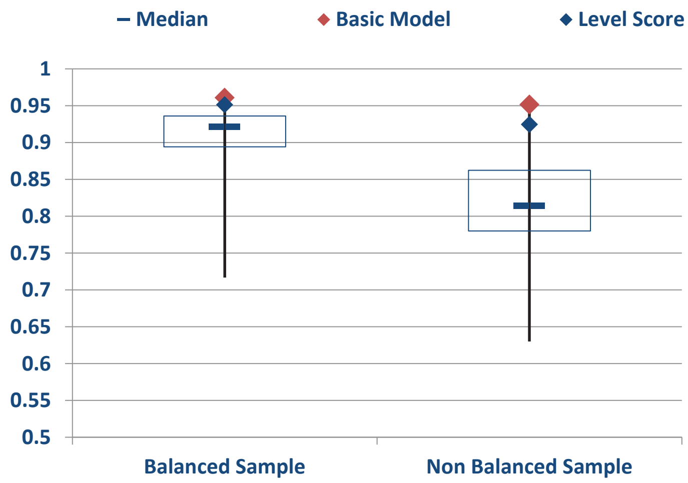

Figure 6: Distribution of ROC areas including all three-variable combinations, a basic model, and the aggregate vulnerability score - quantitative crises dataset

Note: AUROC scores distribution across models: black line from minimum score to maximum, boxes for 50% of the distribution between the first quartile (25) and the third (75).

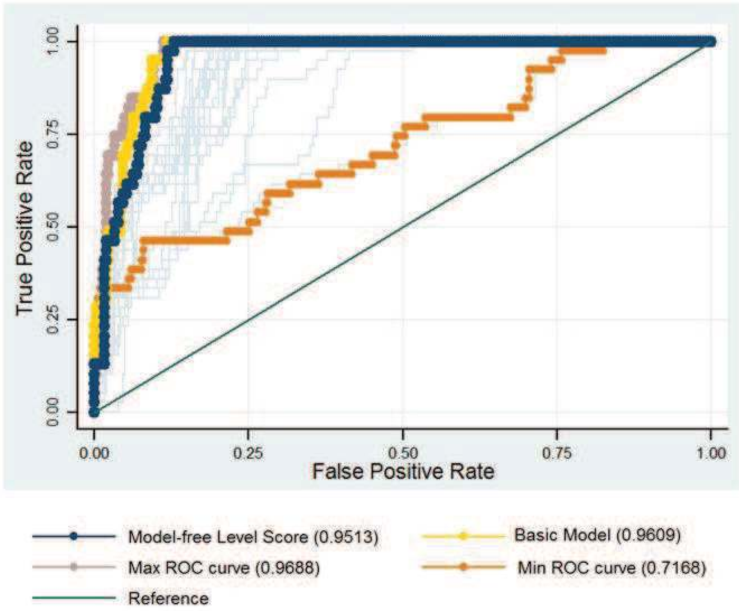

Figure 7: ROC curves of the model-free level score, the Basic model, and all three-variable combinations - quantitative crises dataset
NOTE: Basic model comprises price to income ratio, overvaluation, debt service ratio, household leverage and lending spreads; the max (min) ROC curve is the best (worst) performing model from all three-variable combinations (see Annex C).

	Obs	ROC Area	Std. Err.	-Asymptotic Normal-- [95% Conf. Interval]	
Level_score	307	0.9598	0.0104	0.93943	0.98009
Basic_Model	307	0.9943	0.003	0.9884	1
OP_Model	307	0.9565	0.0114	0.93411	0.9788

Table 6: ROC areas of two selected models and the model-free level score - quantitative crises dataset
NOTE: The table presents the comparison of ROC areas for the level score, basic model and the best model in Ferrari, Pirovano, and Cornacchia (2015) (labelled OPModel).

4 Conclusion

In view of the importance of real estate in the balance sheets of households and credit institutions, as well as experiences of real estate-related crises in a number of countries in the past years, this paper proposes a framework for monitoring vulnerabilities related to the residential real estate sector in a cross-country context.

We use a selection of main indicators related to three key dimensions of the real estate sector vulnerabilities: real estate valuation, household indebtedness and bank credit cycle. To monitor the developments across countries and time, we aggregate the indicators into an average vulnerability measure. Our approach not only allows for assessing the level of vulnerabilities at a given point in time, but also for tracking the broad developments in the real estate-related vulnerabilities, also in terms of particular dimensions. The advantage of the proposed measure, in comparison to model-based approaches, is the ability to account for a number of relevant indicators while not being constrained by small-sample problems resulting in the modelling sensitivity to estimation errors and coefficient instability over time. The monitoring in this context allows for a simple and transparent analysis of the vulnerabilities across different dimensions, provides a cross-check of consistency of signals from several indicators, and accounts for the developments in terms of the levels and dynamics.

Historically, the aggregated vulnerability score for the monitoring framework proves to be an informative predictor of residential real estate-related crises. Importantly, the aggregate measure performs better than most model-based indicator estimates, even when models are estimated based on very favourable in-sample conditions. Given advantages of the simple model-free approach to constructing vulnerability scores, the results of this paper show that a simple monitoring framework is a useful complement to model-based approaches for analysing vulnerabilities in the residential real estate sector.

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Annex A: Short review of early warning signalling approach

An important strand in the economics literature has the 90's focused on building theoretical frameworks and producing empirical evidence of the determinants of crises, starting with currency crises (Frankel and Rose (1996), Kaminsky and Reinhart (1999)), banking crises (Demirgüc-Kunt and Detragiache (1998), Babecky et al. (2012), Drehmann and Juselius (2012), Behn et al. (2013)), before expanding to a broader range of events. More specifically, this literature has tried to find early warning indicators able to provide in ex-ante signals on vulnerabilities. Depending on the type of crisis analysed and the purpose of the early warning model (horizon and type of policymaking: conduct of monetary policy, the setting of the countercyclical capital buffer, or in the present paper the mitigation of real estate vulnerabilities), different sets of indicators have been found to be good predictors of crises.

The most common way of selecting the best indicators in the literature has been the signalling approach, initiated first by Kaminsky, Lizondo, and Reinhart (1998) and developed subsequently: a relevant predicting horizon prior to the crisis is defined, and the signals issued by the uni- or multivariate models when breaching specific thresholds in the defined pre-crisis period are compared to the actual situation. The resulting signal could then be classified in four different ways: correctly predicting a crisis (A), issuing a signal when no crisis happened (B), missing a crisis which actually happened (C), correctly assessing the absence of crisis (D). The classification is summarized in the following so-called 'Confusion matrix':

	Crisis	**No crisis**
Signal is issued	A	B
Signal is not issued	C	D

Table A-1: Confusion matrix

NOTE: The table presents the confusion matrix.

A variety of statistics - Area Under the Receiving Operating Curve (AUROC), true and false positive rates, noise ratio and policymakers loss functions can then be computed to define the best indicators as well as the optimal thresholds to predict the corresponding crises.

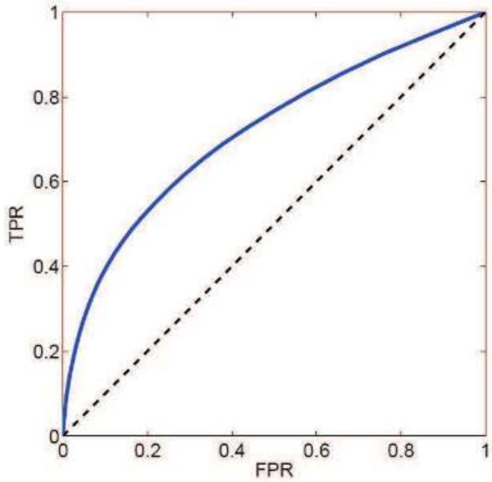

Figure A-1: ROC curve

NOTE: The figure presents an example of a ROC curve.

Annex B: Crises data samples

Country	Start Crisis	End crisis	Length
Austria			-
Belgium			-
Bulgaria			-
Croatia			-
Cyprus			-
Czech Republic			
Denmark	1987Q1	1993Q4	28
	2008Q3	Ongoing	19
Estonia			-
Finland	1991Q3	1995Q4	18
France	1993Q3	1995Q4	10
Germany			-
Greece			-
Hungary	2008Q3	Ongoing	19
Ireland	2008Q3	Ongoing	19
Italy			-
Latvia	2008Q4	2010Q3	8
Lithuania	2008Q4	2010Q4	9
Luxembourg			-
Malta			-
Netherlands	2008Q3	Ongoing	19
Poland			-
Portugal			-
Romania			-
Slovakia			-
Slovenia	2008Q1	Ongoing	21
Spain	2009Q2	2013Q1	16
Sweden	1990Q3	1993Q4	14
	2008Q3	2010Q4	10
United Kingdom	1990Q3	1994Q3	17
	2007Q3	Ongoing	23

Country	Start Crisis	End crisis	Length
Austria			-
Belgium			-
Bulgaria			-
Croatia			-
Cyprus			-
Czech Republic			-
Denmark	2008Q1	2009Q3	7
Estonia	2007Q2	2009Q4	11
Finland			-
France			-
Germany			-
Greece	2009Q4	2013Q2	15
Hungary	2008Q4	2009Q4	5
	2010Q4	2012Q4	8
Ireland	2007Q4	2012Q3	20
Italy			-
Latvia	2007Q4	2010Q1	10
Lithuania	2008Q1	2010Q2	10
Luxembourg			-
Malta			-
Netherlands	2011Q4	2013Q2	7
Poland			-
Portugal	2007Q4	2008Q3	4
	2011Q1	2012Q3	7
Romania			-
Slovakia	2008Q2	2009Q4	7
Slovenia	2008Q3	2009Q4	6
	2012Q1	2012Q4	4
	2013Q3	2014Q2	4
Spain	2010Q4	2013Q2	11
Sweden			-
United Kingdom	2008Q1	2009Q2	6

Table B-1: Crises data samples

Note: The table presents two datasets of crisis dates. The left panel presents Ferrari, Pirovano, and Cornacchia (2015) crisis dates, the right panel presents quantitative house price bust dates.

Annex C: Additional indicators and tests of predictive power

Indicators	Description	Data source	Rationale
Other potential indicators			
Credit for house purchases to GDP gap *(GAPcreditHP_GDP)*	MFIs credit to domestic households for house purchase to GDP (Monthly data), detrended with HP Filter (methodology as in Credit to GDP gap below)	ECB Balance Sheet Items	Credit for house purchases to GDP highlighted by ESRB (2016) ; Büyükkarabacak and Valev (2010); gap as a widely-used indicators of excessive credit growth
Credit to GDP Gap *(TC_Gap)*	Total Credit to private non-financial sector to GDP, detrended with HP Filter of lambda=400 000	EC, BIS, ECB and ECB calculations, published in ESRB Risk Dashboard	Highlighted by Drehmann & Juselius 2012, various BIS work
Lending margins *(lendingmargins)*	Lending margins of MFIs on new loans to households for house purchase (difference btw. MFIs' interest rates for new business loans and a weighted average rate of new deposits from HHs and NFCs)	ECB, published in ESRB Risk Dashboard	Indicating banks' pricing of loans, as compared to the cost of deposits.

Table C-1: Additional indicators

NOTE: The table summarises additional indicators included for robustness reasons.

VARIABLES	(1) Logit coeff	(2) Logit coeff	(3) Logit coeff	(4) Logit coeff	(5) Logit coeff	(6) Logit coeff	(7) Logit coeff	(8) Logit coeff	(9) Logit coeff
PTI_L1	0.0918***	0.101***	0.104***	0.0897***	0.103***	0.150***	0.0814***	0.0854***	0.0822***
	(0.0115)	(0.0125)	(0.0125)	(0.0120)	(0.0137)	(0.0218)	(0.0104)	(0.0121)	(0.0108)
PTR_L1									
overval_L1									
DSR_L1	0.278***	0.284***	0.274***	0.257***	0.252***	0.318***			
	(0.0340)	(0.0595)	(0.0356)	(0.0370)	(0.0297)	(0.0397)			
DTI_L1							0.0145***	0.0161***	0.00901*
							(0.00400)	(0.00613)	(0.00543)
HHlev_L1									
lendingspreads_L1	-0.548***						-0.542***		
	(0.152)						(0.126)		
creditHP_GDP_L1		-0.669						-1.398	
		(1.038)						(1.738)	
loan_deposit_L1			-0.00305						0.00393
			(0.00234)						(0.00379)
GAPcreditHP_GDP_L1				3.098					
				(4.724)					
TC_GAP_L1					0.00288				
					(0.00837)				
lendingmargins_L1						-0.891***			
						(0.307)			
Constant	-13.47***	-15.21***	-15.33***	-14.16***	-15.50***	-19.29***	-10.85***	-11.96***	-12.02***
	(1.340)	(1.388)	(1.400)	(1.375)	(1.555)	(2.510)	(1.283)	(1.379)	(1.203)
Observations	560	609	626	562	628	482	549	606	613
Pseudo R2	0.3349	0.3124	0.3134	0.2957	0.3102	0.397	0.2056	0.1449	0.1493
AUROC	0.8892	0.8852	0.8868	0.8789	0.8871	0.923	0.796	0.7803	0.8026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-2: Results of all possible three-variable regressions - quantitative crises dataset
NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(10) Logit coeff	(11) Logit coeff	(12) Logit coeff	(13) Logit coeff	(14) Logit coeff	(15) Logit coeff	(16) Logit coeff	(17) Logit coeff	(18) Logit coeff
PTI_L1	0.0685***	0.0883***	0.123***	0.0808***	0.0855***	0.0896***	0.0804***	0.0854***	0.127***
	(0.0106)	(0.00981)	(0.0174)	(0.00897)	(0.00990)	(0.0102)	(0.00983)	(0.00894)	(0.0184)
PTR_L1									
overval_L1									
DSR_L1									
DTI_L1	0.0128***	0.0111***	0.0141***						
	(0.00445)	(0.00348)	(0.00474)						
HHlev_L1				4.102***	4.512***	3.234**	6.098***	4.195***	6.474***
				(1.422)	(1.347)	(1.578)	(1.709)	(1.429)	(1.810)
lendingspreads_L1				-0.234					
				(0.143)					
creditHP_GDP_L1					-0.0507				
					(0.982)				
loan_deposit_L1						0.00792***			
						(0.00182)			
GAPcreditHP_GDP_L1	8.819**						-0.531		
	(4.412)						(3.159)		
TC_GAP_L1		0.00234						0.00525	
		(0.00713)						(0.00388)	
lendingmargins_L1			-0.863***						0.0103
			(0.244)						(0.229)
Constant	-10.42***	-12.29***	-14.65***	-11.22***	-12.40***	-13.52***	-12.64***	-12.31***	-17.23***
	(1.319)	(1.206)	(2.026)	(1.050)	(1.188)	(1.177)	(1.273)	(0.983)	(2.227)
Observations	561	621	498	631	703	710	656	718	556
Pseudo R2	0.114	0.2003	0.2231	0.2146	0.1801	0.197	0.182	0.2206	0.1896
AUROC	0.753	0.8184	0.8087	0.8043	0.8138	0.8226	0.8022	0.8335	0.8107

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-3: Results of all possible three-variable regressions - quantitative crises dataset, cont.

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(19) Logit coeff	(20) Logit coeff	(21) Logit coeff	(22) Logit coeff	(23) Logit coeff	(24) Logit coeff	(25) Logit coeff	(26) Logit coeff	(27) Logit coeff
PTI_L1									
PTR_L1	0.0885***	0.101***	0.104***	0.109***	0.104***	0.107***	0.0740***	0.101***	0.0942***
	(0.0117)	(0.0122)	(0.0119)	(0.0149)	(0.0135)	(0.0153)	(0.0117)	(0.0120)	(0.0112)
overval_L1									
DSR_L1	0.258***	0.237***	0.252***	0.240***	0.239***	0.300***			
	(0.0327)	(0.0615)	(0.0346)	(0.0352)	(0.0282)	(0.0412)			
DTI_L1							0.0133***	0.0196***	0.0108**
							(0.00388)	(0.00577)	(0.00552)
HHlev_L1									
lendingspreads_L1	-0.454***						-0.500***		
	(0.157)						(0.117)		
creditHP_GDP_L1		0.120						-2.206	
		(1.102)						(1.710)	
loan_deposit_L1			-0.00205						0.00186
			(0.00248)						(0.00386)
GAPcreditHP_GDP_L1				-0.658					
				(4.709)					
TC_GAP_L1					0.000886				
					(0.00812)				
lendingmargins_L1						-0.948***			
						(0.314)			
Constant	-13.00***	-15.05***	-15.12***	-16.10***	-15.39***	-14.55***	-9.773***	-13.44***	-12.98***
	(1.372)	(1.347)	(1.363)	(1.673)	(1.509)	(1.794)	(1.432)	(1.375)	(1.268)
Observations	560	609	626	562	628	482	549	606	613
Pseudo R2	0.32	0.3046	0.3084	0.323	0.3074	0.3518	0.1742	0.1858	0.185
AUROC	0.8954	0.8838	0.8861	0.8898	0.8855	0.9133	0.7837	0.8015	0.8148

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-4: Results of all possible three-variable regressions - quantitative crises dataset, cont.

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(28) Logit coeff	(29) Logit coeff	(30) Logit coeff	(31) Logit coeff	(32) Logit coeff	(33) Logit coeff	(34) Logit coeff	(35) Logit coeff	(36) Logit coeff
PTI_L1									
PTR_L1	0.0935***	0.0855***	0.114***	0.0872***	0.0919***	0.0941***	0.105***	0.0936***	0.116***
	(0.0118)	(0.0121)	(0.0139)	(0.0101)	(0.00997)	(0.0103)	(0.0128)	(0.00991)	(0.0126)
overval_L1									
DSR_L1									
DTI_L1	0.0105**	0.00830**	0.0143***						
	(0.00472)	(0.00337)	(0.00500)						
HHlev_L1				4.786***	5.581***	4.258***	7.385***	5.324***	5.921***
				(1.523)	(1.476)	(1.631)	(1.881)	(1.537)	(1.797)
lendingspreads_L1				-0.125					
				(0.146)					
creditHP_GDP_L1					-0.399				
					(1.167)				
loan_deposit_L1						0.00618***			
						(0.00195)			
GAPcreditHP_GDP_L1	1.483						-6.909**		
	(4.308)						(3.328)		
TC_GAP_L1		-0.00657						-0.00218	
		(0.00723)						(0.00439)	
lendingmargins_L1			-0.882***						-0.122
			(0.268)						(0.232)
Constant	-12.73***	-11.33***	-13.59***	-12.19***	-13.14***	-13.94***	-15.64***	-13.38***	-15.48***
	(1.454)	(1.363)	(1.706)	(1.279)	(1.238)	(1.282)	(1.744)	(1.191)	(1.604)
Observations	561	621	498	586	657	664	612	664	550
Pseudo R2	0.1728	0.1429	0.2371	0.1851	0.1947	0.2058	0.2317	0.1974	0.2186
AUROC	0.8001	0.7789	0.8297	0.8008	0.8151	0.8173	0.8364	0.8165	0.8173

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-5: Results of all possible three-variable regressions - quantitative crises dataset, cont.

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(37) Logit coeff	(38) Logit coeff	(39) Logit coeff	(40) Logit coeff	(41) Logit coeff	(42) Logit coeff	(43) Logit coeff	(44) Logit coeff	(45) Logit coeff
PTI_L1									
PTR_L1									
overval_L1	0.0675***	0.0768***	0.0798***	0.0620***	0.0729***	0.0460***	0.0714***	0.0658***	0.0641***
	(0.0161)	(0.0146)	(0.0151)	(0.0168)	(0.0167)	(0.0169)	(0.0115)	(0.0124)	(0.0112)
DSR_L1	0.237***	0.175***	0.209***	0.216***	0.215***	0.286***			
	(0.0272)	(0.0496)	(0.0269)	(0.0303)	(0.0255)	(0.0342)			
DTI_L1							0.00995***	0.00812	0.00467
							(0.00313)	(0.00580)	(0.00418)
HHlev_L1									
lendingspreads_L1	-0.506***						-0.474***		
	(0.134)						(0.102)		
creditHP_GDP_L1		0.996						-0.547	
		(0.907)						(1.806)	
loan_deposit_L1			-0.000482						0.00324
			(0.00197)						(0.00293)
GAPcreditHP_GDP_L1				1.983					
				(4.141)					
TC_GAP_L1					0.0206**				
					(0.00848)				
lendingmargins_L1						-0.999***			
						(0.291)			
Constant	-3.976***	-4.942***	-4.781***	-4.812***	-5.069***	-3.601***	-2.296***	-2.936***	-3.261***
	(0.439)	(0.381)	(0.434)	(0.405)	(0.402)	(0.545)	(0.382)	(0.379)	(0.280)
Observations	560	609	626	562	628	482	584	647	654
Pseudo R2	0.2886	0.2518	0.2459	0.233	0.2572	0.2724	0.1735	0.101	0.1042
AUROC	0.858	0.8233	0.8085	0.8057	0.8359	0.8669	0.7468	0.6817	0.7057

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-6: Results of all possible three-variable regressions - quantitative crises dataset, cont.

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(46) Logit coeff	(47) Logit coeff	(48) Logit coeff	(49) Logit coeff	(50) Logit coeff	(51) Logit coeff	(52) Logit coeff	(53) Logit coeff	(54) Logit coeff
PTI_L1									
PTR_L1									
overval_L1	0.0564***	0.0779***	0.0554***	0.0512***	0.0584***	0.0519***	0.0479***	0.0482***	0.0700***
	(0.0137)	(0.0138)	(0.0117)	(0.00935)	(0.00976)	(0.00965)	(0.0107)	(0.00943)	(0.00935)
DSR_L1									
DTI_L1	0.00466	0.00454	0.0108***						
	(0.00368)	(0.00308)	(0.00359)						
HHlev_L1				2.302**	3.822***	1.403	2.163*	3.119***	5.911***
				(1.096)	(1.003)	(1.227)	(1.219)	(1.051)	(1.213)
lendingspreads_L1				-0.388***					
				(0.101)					
creditHP_GDP_L1					-2.029**				
					(0.866)				
loan_deposit_L1						0.00456***			
						(0.00152)			
GAPcreditHP_GDP_L1	-0.980						-0.939		
	(3.848)						(2.479)		
TC_GAP_L1		-0.000946						0.0102***	
		(0.00863)						(0.00386)	
lendingmargins_L1			-0.757***						0.0966
			(0.206)						(0.148)
Constant	-2.822***	-2.776***	-2.132***	-1.893***	-2.745***	-3.244***	-2.916***	-3.117***	-4.538***
	(0.393)	(0.375)	(0.513)	(0.479)	(0.465)	(0.451)	(0.467)	(0.407)	(0.594)
Observations	602	639	534	750	872	879	818	876	696
Pseudo R2	0.07	0.1261	0.1555	0.1115	0.0824	0.0761	0.0554	0.0804	0.1287
AUROC	0.63	0.7085	0.7624	0.717	0.7085	0.6946	0.6399	0.6885	0.7301

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-7: Results of all possible three-variable regressions - quantitative crises dataset, cont.

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

Annex D: Robustness check: results using the qualitative crises dataset

VARIABLES	(1) Logit coeff	(2) Logit coeff	(3) Logit coeff	(4) Logit coeff	(5) Logit coeff	(6) Logit coeff	(7) Logit coeff	(8) Logit coeff	(9) Logit coeff
PTI_L1	0.0625***								
	(0.00780)								
PTR_L1		0.0628***							
		(0.00855)							
overval_L1			0.0762***						
			(0.00794)						
DSR_L1				0.359***					
				(0.0300)					
DTI_L1					0.0338***				
					(0.00922)				
HHlev_L1						1.473			
						(1.113)			
creditHP_GDP_L1							3.956***		
							(0.622)		
lendingspreads_L1								-0.579***	
								(0.102)	
loan_deposit_L1									0.0190***
									(0.00179)
Constant	-8.760***	-8.740***	-2.750***	-5.896***	-5.863***	-2.682***	-3.755***	-1.163***	-4.976***
	(0.843)	(0.918)	(0.131)	(0.361)	(1.032)	(0.389)	(0.291)	(0.190)	(0.285)
Observations	921	864	1,286	556	608	843	1,201	1,073	1,206
Pseudo R2	0.1951	0.1321	0.1376	0.2987	0.1163	0.0033	0.0847	0.0808	0.1456
AUROC	0.8312	0.7682	0.7641	0.9130	0.7601	0.5191	0.6592	0.7587	0.7731
Type I Error #	27.45%	30.49%	34.17%	16.67%	21.74%	66.67%	34.26%	17.95%	49.07%
Type II Error #	20.39%	24.30%	24.70%	14.52%	15.48%	48.62%	27.17%	41.42%	16.58%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-1: Results of univariate regressions - qualitative crises dataset

NOTE: The table presents the coefficients of univariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Logit coeff	Logit coeff	Logit coeff	Logit coeff	Logit coeff	Logit coeff	Logit coeff	Logit coeff	Logit coeff
PTI_L1	0.0505**	0.0582***	0.0729***	0.0479***	0.0774***	0.0648***	0.00251	0.0572***	0.0473***
	(0.0213)	(0.0125)	(0.0118)	(0.0163)	(0.0156)	(0.0249)	(0.00769)	(0.0133)	(0.0105)
PTR_L1									
overval_L1									
DSR_L1	0.647***	0.554***	0.350***	0.535***	0.391***	0.618***			
	(0.0771)	(0.0759)	(0.0529)	(0.0611)	(0.0389)	(0.0679)			
DTI_L1							0.0777***	0.0977***	0.0304
							(0.0219)	(0.0132)	(0.0218)
HHlev_L1									
lendingspreads_L1	-2.440***						-0.653***		
	(0.427)						(0.136)		
creditHP_GDP_L1		-2.735						-11.79***	
		(1.815)						(2.496)	
loan_deposit_L1			0.00758*						0.0137
			(0.00427)						(0.00971)
GAPcreditHP_GDP_L1				41.48***					
				(9.013)					
TC_GAP_L1					-0.0125				
					(0.0167)				
lendingmargins_L1						-2.211***			
						(0.384)			
Constant	-10.84***	-12.43***	-14.45***	-12.56***	-14.02***	-11.93***	-9.957***	-13.89***	-12.67***
	(2.543)	(1.551)	(1.414)	(2.105)	(1.907)	(2.925)	(2.326)	(1.734)	(1.389)
Observations	487	536	553	503	555	409	480	535	542
Pseudo R2	0.6061	0.4096	0.3837	0.4856	0.3688	0.5349	0.3876	0.2848	0.2511
AUROC	0.9646	0.9148	0.9088	0.9475	0.8898	0.9408	0.8715	0.8684	0.8653

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-2: Results of all possible three-variable regressions - qualitative crises dataset

Note: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(10) Logit coeff	(11) Logit coeff	(12) Logit coeff	(13) Logit coeff	(14) Logit coeff	(15) Logit coeff	(16) Logit coeff	(17) Logit coeff	(18) Logit coeff
PTI_L1	0.0265	0.0150**	0.0680***	0.0841***	0.0841***	0.103***	0.0878***	0.0846***	0.0931***
	(0.0173)	(0.00589)	(0.0191)	(0.00950)	(0.00933)	(0.00985)	(0.0122)	(0.00845)	(0.0181)
PTR_L1									
overval_L1									
DSR_L1									
DTI_L1	0.0490***	0.0487***	0.0404***						
	(0.0168)	(0.0109)	(0.0102)						
HHlev_L1				-3.866**	-6.937***	-8.780***	-4.058**	-3.032**	-3.389*
				(1.816)	(2.064)	(2.391)	(1.981)	(1.491)	(1.831)
lendingspreads_L1				-1.140***					
				(0.196)					
creditHP_GDP_L1					3.825**				
					(1.665)				
loan_deposit_L1						0.0300***			
						(0.00366)			
GAPcreditHP_GDP_L1	69.59***						43.84***		
	(12.55)						(6.129)		
TC_GAP_L1		0.0231**						0.00948	
		(0.0107)						(0.00598)	
lendingmargins_L1			-0.312*						-0.390
			(0.182)						(0.283)
Constant	-10.54***	-9.407***	-13.10***	-7.923***	-10.18***	-14.51***	-10.45***	-10.11***	-10.01***
	(1.418)	(1.343)	(1.925)	(1.036)	(1.112)	(1.301)	(1.426)	(0.833)	(2.001)
Observations	502	554	420	540	612	619	579	629	464
Pseudo R2	0.3673	0.2302	0.2259	0.3546	0.1913	0.3576	0.2797	0.2574	0.0891
AUROC	0.8586	0.8384	0.8299	0.8766	0.7982	0.9104	0.8327	0.8282	0.735

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-3: Results of all possible three-variable regressions - qualitative crises dataset

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(19) Logit coeff	(20) Logit coeff	(21) Logit coeff	(22) Logit coeff	(23) Logit coeff	(24) Logit coeff	(25) Logit coeff	(26) Logit coeff	(27) Logit coeff
PTI_L1									
PTR_L1	0.0130	0.0434***	0.0669***	0.0419	0.0690***	0.0400	0.0277*	0.0607***	0.0401***
	(0.0246)	(0.0162)	(0.0157)	(0.0262)	(0.0147)	(0.0270)	(0.0148)	(0.0171)	(0.0154)
overval_L1									
DSR_L1	0.641***	0.484***	0.326***	0.500***	0.372***	0.620***			
	(0.0791)	(0.0719)	(0.0479)	(0.0494)	(0.0333)	(0.0672)			
DTI_L1							0.0762***	0.0992***	0.0270
							(0.0225)	(0.0125)	(0.0253)
HHlev_L1									
lendingspreads_L1	-2.548***						-0.645***		
	(0.468)						(0.121)		
creditHP_GDP_L1		-1.679						-12.83***	
		(1.650)						(2.139)	
loan_deposit_L1			0.00828**						0.0134
			(0.00412)						(0.0118)
GAPcreditHP_GDP_L1				38.73***					
				(8.391)					
TC_GAP_L1					-0.0105				
					(0.0131)				
lendingmargins_L1						-2.349***			
						(0.412)			
Constant	-6.826***	-10.64***	-13.65***	-11.61***	-12.89***	-9.214***	-12.33***	-13.80***	-11.39***
	(2.513)	(1.814)	(1.868)	(2.979)	(1.823)	(2.928)	(2.459)	(1.814)	(1.326)
Observations	487	536	553	503	555	409	480	535	542
Pseudo R2	0.5942	0.3913	0.3792	0.4807	0.3624	0.5262	0.3965	0.2856	0.2435
AUROC	0.9621	0.914	0.9004	0.9429	0.8811	0.9403	0.8745	0.8869	0.8649

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-4: Results of all possible three-variable regressions - qualitative crises dataset
NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(28) Logit coeff	(29) Logit coeff	(30) Logit coeff	(31) Logit coeff	(32) Logit coeff	(33) Logit coeff	(34) Logit coeff	(35) Logit coeff	(36) Logit coeff
PTI_L1									
PTR_L1	0.00708	0.0208	0.0386**	0.0718***	0.0639***	0.0813***	0.0754***	0.0593***	0.0866***
	(0.0212)	(0.0144)	(0.0193)	(0.0171)	(0.0148)	(0.0140)	(0.0222)	(0.0122)	(0.0195)
overval_L1									
DSR_L1									
DTI_L1	0.0492***	0.0468***	0.0382***						
	(0.0180)	(0.0114)	(0.0104)						
HHlev_L1				-3.520**	-6.139***	-7.471***	-2.945	-2.519*	-3.460**
				(1.727)	(1.923)	(2.170)	(2.034)	(1.393)	(1.562)
lendingspreads_L1				-0.967***					
				(0.178)					
creditHP_GDP_L1					4.568**				
					(2.034)				
loan_deposit_L1						0.0271***			
						(0.00404)			
GAPcreditHP_GDP_L1	68.78***						37.27***		
	(13.94)						(5.181)		
TC_GAP_L1		0.0175						0.0101**	
		(0.0116)						(0.00508)	
lendingmargins_L1			-0.362*						-0.495**
			(0.198)						(0.249)
Constant	-8.587***	-9.664***	-9.678***	-6.881***	-8.542***	-12.12***	-9.430***	-7.551***	-9.035***
	(1.303)	(1.218)	(1.680)	(1.760)	(1.442)	(1.627)	(2.301)	(1.259)	(2.182)
Observations	502	554	420	492	565	572	534	572	458
Pseudo R2	0.3613	0.2302	0.2049	0.1805	0.1145	0.2689	0.1915	0.0932	0.1012
AUROC	0.8451	0.8382	0.8235	0.8256	0.7601	0.8793	0.7792	0.7221	0.7521

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-5: Results of all possible three-variable regressions - qualitative crises dataset

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(37) Logit coeff	(38) Logit coeff	(39) Logit coeff	(40) Logit coeff	(41) Logit coeff	(42) Logit coeff	(43) Logit coeff	(44) Logit coeff	(45) Logit coeff
PTI_L1									
PTR_L1									
overval_L1	0.111***	0.127***	0.128***	0.0811***	0.138***	0.0767***	0.0550***	0.0979***	0.0714***
	(0.0308)	(0.0252)	(0.0240)	(0.0249)	(0.0230)	(0.0205)	(0.0113)	(0.0163)	(0.0131)
DSR_L1	0.661***	0.656***	0.355***	0.496***	0.390***	0.602***			
	(0.0828)	(0.0906)	(0.0587)	(0.0454)	(0.0372)	(0.0644)			
DTI_L1							0.0452***	0.0848***	0.00161
							(0.0154)	(0.0114)	(0.0166)
HHlev_L1									
lendingspreads_L1	-2.250***						-0.504***		
	(0.453)						(0.101)		
creditHP_GDP_L1		-5.279***						-15.37***	
		(1.772)						(1.985)	
loan_deposit_L1			0.00586						0.0183*
			(0.00418)						(0.00941)
GAPcreditHP_GDP_L1				31.04***					
				(6.900)					
TC_GAP_L1					-0.0183				
					(0.0116)				
lendingmargins_L1						-2.143***			
						(0.351)			
Constant	-6.655***	-7.164***	-7.637***	-7.812***	-6.943***	-5.713***	-6.313***	-5.579***	-5.639***
	(0.894)	(0.680)	(0.488)	(0.717)	(0.679)	(0.699)	(1.721)	(0.851)	(0.733)
Observations	487	536	553	503	555	409	515	576	583
Pseudo R2	0.6737	0.5104	0.4858	0.5266	0.4798	0.5778	0.3125	0.2672	0.2304
AUROC	0.974	0.9162	0.9201	0.9423	0.8974	0.9521	0.808	0.8609	0.8617

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-6: Results of all possible three-variable regressions - qualitative crises dataset

NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

VARIABLES	(46) Logit coeff	(47) Logit coeff	(48) Logit coeff	(49) Logit coeff	(50) Logit coeff	(51) Logit coeff	(52) Logit coeff	(53) Logit coeff	(54) Logit coeff
PTI_L1									
PTR_L1									
overval_L1	0.0113	0.0501***	0.0731***	0.0841***	0.0825***	0.0732***	0.0680***	0.0822***	0.0937***
	(0.0193)	(0.0120)	(0.0187)	(0.0119)	(0.0117)	(0.0104)	(0.0114)	(0.0106)	(0.0142)
DSR_L1									
DTI_L1	0.0260*	0.0258***	0.0310***						
	(0.0136)	(0.00917)	(0.00937)						
HHlev_L1				-2.010	-1.412	-6.304***	-3.708***	0.716	-0.185
				(1.223)	(1.061)	(1.287)	(1.188)	(1.046)	(1.169)
lendingspreads_L1				-0.742***					
				(0.153)					
creditHP_GDP_L1					-1.264				
					(1.219)				
loan_deposit_L1						0.0193***			
						(0.00325)			
GAPcreditHP_GDP_L1	57.05***						20.55***		
	(10.85)						(3.160)		
TC_GAP_L1		0.00851						0.00739*	
		(0.00821)						(0.00393)	
lendingmargins_L1			-0.266						0.0353
			(0.172)						(0.174)
Constant	-5.237***	-5.292***	-5.535***	-0.450	-1.761***	-3.290***	-1.525***	-2.789***	-2.855***
	(1.383)	(0.992)	(0.939)	(0.588)	(0.480)	(0.530)	(0.460)	(0.441)	(0.666)
Observations	543	572	456	659	781	788	741	787	604
Pseudo R2	0.2385	0.1629	0.2838	0.2631	0.152	0.2318	0.1562	0.1585	0.1638
AUROC	0.7649	0.749	0.8446	0.832	0.7715	0.8717	0.7717	0.7333	0.7713

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D-7: Results of all possible three-variable regressions - qualitative crises dataset
NOTE: The table presents the coefficients of multivariate regressions. The stars report the significance of coefficients (*** at 99%, ** at 95% and * at 90% confidence levels, respectively).

	Obs	ROC Area	Std. Err.	—Asymptotic Normal— [95% Conf.	Interval]
Level_score	420	0.9414	0.0110	0.91982	0.96291
Basic_Mode~t	420	0.8487	0.0251	0.79947	0.89786
OP_Model	420	0.8827	0.0228	0.83804	0.92743
max	420	0.8563	0.0243	0.80870	0.90399

Ho: area(**Level_score**) = area(**Basic_Mode~t**) = area(**OP_Model**) = area(**max**)
chi2(**3**) = **28.35** Prob>chi2 = **0.0000**

Table D-8: Comparison between the monitoring framework and model-based approaches - qualitative crises dataset

NOTE: The table presents the comparison of ROC values for selected models and the level score.

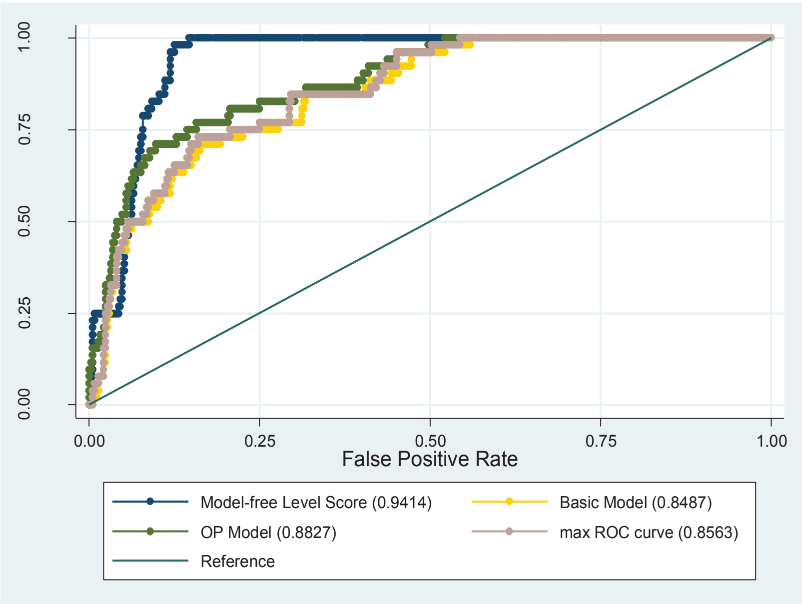

Figure D-1: ROC curves of the model-free level score and model based approaches - qualitative crises dataset

NOTE: Basic model is comprising overvaluation, price to income, debt service ratio, lending spreads; OP model is the best model highlighted from Ferrari, Pirovano, and Cornacchia (2015), the max ROC curve is the best performing model from all three-variable combinations (see above).

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