Sensitivity of credit risk stress test results: Modelling issues with an application to Belgium

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Abstract

This paper assesses the sensitivity of solvency stress testing results to the choice of credit risk variable and level of data aggregation at which the stress test is conducted. In practice, both choices are often determined by technical considerations, such as data availability. Using data for the Belgian banking system, we find that the impact of a stress test on banks' Tier 1 ratios can differ substantially depending on the credit risk variable and the level of data aggregation considered. If solvency stress tests are going to be used as a supervisory tool or to set regulatory capital requirements, there is a need to further harmonise their execution across institutions and supervisors in order to enhance comparability. This is certainly relevant in the context of the EU-wide stress tests, where institutions often use different credit risk variables and levels of data aggregation to estimate the impact of the common methodology and macroeconomic scenario on their capital level while supervisors rely on different models to quality assure and validate banks' results. More generally, there is also a need to improve the availability and quality of the data to be used for stress testing purposes.

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1. Introduction

Following the 2007-2008 financial crisis, stress testing exercises have gained in importance as a tool for assessing vulnerabilities in the financial sector. At the international level, the IMF has developed balance sheet type solvency and liquidity stress testing tools, which are used as key components of its Financial Stability Assessment Program (FSAP).[1] At the EU level, the European Banking Authority (EBA) now conducts regular solvency stress testing exercises which complement the supervisory authorities' analyses with an EU-wide perspective by using a common stress test methodology and macroeconomic scenario. While until recently these large-scale assessments of EU banks' resilience primarily aimed at boosting market confidence and reducing uncertainties surrounding major banks' fragilities, they now strive more explicitly to inform the Supervisory Review and Evaluation Process (SREP) of EU banks, under which decisions are made on appropriate capital resources and forward-looking capital plans are challenged.[2]

This paper investigates the sensitivity of solvency stress testing results across different modelling choices and stresses the need for even more harmonisation in the execution of solvency stress tests if these are going to be used as a supervisory tool (e.g. for Pillar 2 decisions via the SREP) or to set regulatory requirements (e.g. for systemically important banks). Solvency stress tests provide estimates of the impact of stressed macroeconomic scenarios on banks' capital. The macroeconomic stress is likely to have an impact on the components of the profit and loss account (P&L), which through retained earnings have an impact on the capital and therefore the solvency position of banks' balance sheets. Despite ongoing efforts to incorporate assessments of multiple types of risks and of second-round effects in stress testing frameworks, credit risk remains the main type of bank risk that is assessed in bank supervisory authorities' solvency stress testing exercises.[3] As a consequence, most stress testing exercises concentrate on impairments in banks' loan portfolios (as opposed, for example, to securities held for trading purposes).

In considering the impact of a stressed macroeconomic scenario on banks' loan impairments, the critical question that must be addressed by those conducting the stress test is how to measure the impact of the stressed macroeconomic variables on credit risk associated with the loan portfolio. Ideally, one would want to translate shocks to macroeconomic variables into an increase in expected losses on the portfolio. However, there are no unanimously accepted techniques for making such estimates. As a result, a number of modelling decisions must be made in the course of a stress test. These decisions thus obviously introduce model risk into the results of stress tests (i.e., into the estimated impact on banks).

This paper considers the impact of two basic modelling decisions in stress testing credit risk: (i) Which variable to use for measuring credit risk (e.g., non-performing loans, loan loss provisions, bankruptcy rates), and (ii) At what level of data aggregation to conduct the stress test (e.g., bank level, sectoral level, economy-wide level). While these questions may seem elementary, practitioners' modelling choices and practical issues such as data availability have resulted in

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[1] See Schmieder *et al.* (2011 and 2012).

[2] See EBA (2015) and ECB (2016).

[3] Examples of models covering several risks and/or second-round effects include Boss *et al.* (2006), Aikman *et al.* (2009), Alessandri *et al.* (2009), Gauthier *et al.* (2010), Bruneau *et al.* (2012), and ECB (2017). At the EU level, the EBA stress tests assess multiple risks, with credit risk typically accounting for the biggest impact.

different approaches being taken, both by institutions and supervisors across jurisdictions as well as in the academic literature on stress testing. While considerable effort is being made to extend stress testing frameworks to incorporate assessments of multiple bank risks and second-round effects, we would argue that insufficient attention has been devoted to how the choices on the above questions may affect the practical implementation and results of stress tests. If stress tests are to be actively used in setting capital requirements, more needs to be known about the relative implications of differing modelling choices in the stress testing process.

Using data for the Belgian banking system, we estimate how the choice of different credit risk variables and levels of data aggregation may impact the results of a credit stress test based on the 2014 EBA adverse macroeconomic scenario. We find that both types of modelling choices are important, as they can result in substantial differences in the banks' stressed Tier 1 capital ratios. In particular, in our application, the impact on banks' total Tier 1 capital ratio varies from 0.08 of a percentage point (pp) to -2.93pp depending on the choice of the credit risk variable. Also the level of aggregation of the data used for estimating the values of the credit risk variable (e.g., data at borrower level, bank level, sectoral or economy level) matters: the impact of stressed bankruptcy rates on banks' corporate Tier 1 ratio ranges from -1.10pp when the stress test is conducted at the level of portfolios defined on the basis of industrial sectors to -3.86pp for a portfolio division based on firm size.[4] Depending on the starting level of the banks' solvency position, differences in impact this large may be of crucial importance for the conclusion of the stress test.[5]

Our findings indicate that the questions addressed in this paper may be important issues to be considered in performing a credit risk stress testing exercise. The implication here is that there is a need to further harmonise the conduct of stress tests not only across institutions but also supervisory authorities in order to enhance comparability. This is certainly relevant in the context of the EU-wide stress tests, where institutions often use different credit risk variables and levels of data aggregation to translate the effect of the common methodology and macroeconomic scenario, consequently influencing with this choice the impact that the stress test can have on their Tier 1 capital ratio. Similarly, in order to quality assure and validate banks' results, EU supervisory authorities use their own in-house stress test models, which often differ with respect to the definition and level of data aggregation used for the credit risk variables, thereby potentially also contributing to model risk.[6]

The remainder of the paper is structured as follows. After a brief description of the general stress testing process, section 2 gives an overview of the credit risk variables used for stress testing purposes as well as the different levels of aggregation at which stress tests are being conducted. In section 3, we describe the data and the credit risk model that we use in our application. Section 4

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[4] The corporate Tier 1 ratio refers to the Tier 1 ratio calculated for corporate exposures only. By the term "corporate", we refer to firms of all sizes, including medium-sized and large firms as well as small businesses.

[5] These ranges of impacts are indeed potentially significant given that, in the 2014 EBA stress test, the weighted average impact of credit risk through P&L on Belgian banks' total Tier 1 capital ratio amounted to -2.35pp under the adverse macroeconomic scenario.

[6] Examples of stress test models used by EU supervisory authorities can be found in Feldkircher *et al.* (2013) for Austria, ACPR (2013) for France, Pérez and Trucharte (2013) for Spain, or Burrows, Learmonth and McKeown (2012) for the UK. The framework used by the European Central Bank, which is now responsible for banking supervision in the euro area together with the national competent authorities, is described in ECB (2013) and ECB (2017).

presents the results of our empirical assessment of how the two basic modelling choices may affect stress testing results. Section 5 offers some concluding remarks.

2. The modelling choices

This section first describes the credit stress testing process.[7] We then discuss the two basic questions which are later tested in the paper, namely how the choice of the credit risk variables and the level of data aggregation can affect stress testing results.

2.1 The stress testing process

Credit stress tests assess the impact of a stressed macroeconomic scenario on the quality of banks' credit exposures. This approach essentially consists of three steps, to: (i) forecast values of macroeconomic variables under a given pre-specified (stressed) scenario over a given horizon, (ii) estimate the impact of the stressed macroeconomic variables on the banks' credit risk parameters (typically probability of default and loss given default) over a given horizon, and (iii) use these stressed credit risk parameters to evaluate the impact of the stress scenario on the banks' earnings and risk exposure amounts (REA) and hence on their regulatory capital ratio.[8] A distinction may be made between "top-down" and "bottom-up" stress tests. In their purest forms, the top-down stress test is one in which authorities use data at their disposal to conduct all the steps of the stress test, including estimating the ultimate impact on P&L and solvency positions. In a pure bottom-up stress test, banks estimate the stressed credit risk variables and the ultimate impact on their P&L and solvency.[9]

The practical implementation of steps (i) and (ii) generally involves two different modelling stages. In step (i), a macroeconometric model is typically used for forecasting the behaviour of macroeconomic variables (e.g., the GDP growth rate, the unemployment rate and the long-term interest rate) under a pre-specified stress scenario over a given horizon. In general, adverse shocks to one or more macroeconomic variables are entered into the model, and the equations in the model determine how these and other macroeconomic variables behave over the stress testing horizon as a consequence of the shocks. In Step (ii), a second modelling component, the credit risk model, is required to estimate the impact of the stressed macroeconomic variables on the banks' credit risk parameters over the stress testing horizon. This component essentially consists of one or more equations linking the banks' credit risk parameters to the macroeconomic variables. The stressed macroeconomic variables obtained from the macroeconometric model are entered into this model to obtain stressed values of the credit risk parameters. Finally, in Step (iii), the stressed values of the credit risk parameters are mapped into expected losses, which in turn are entered

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[7] Descriptions of the credit stress testing process and stress testing processes in general can be found in Blaschke *et al.* (2001), Jones, Hilbers and Slack (2004), Čihák (2007), Drehmann (2009), Foglia (2009) and ECB (2013).

[8] The term "risk exposure amounts" has recently replaced the term "risk-weighted assets", which had previously been employed in the Basel framework.

[9] In some jurisdictions, the terms "top-down" and "bottom-up" refer respectively to the aggregate and disaggregate nature of data inputs used by institutions or supervisory authorities rather than to who performs the stress test analysis.

into the banks' P&L, and into changes in banks' REA to obtain the estimated impact on their solvency position.

In this paper, we focus on the second step in which the credit risk variable is linked to the macroeconomic variables.[10] In particular, we test the impact of using different variables for measuring credit risk (i.e., the dependent variable of the credit risk model) and of considering different levels of data aggregation at which the credit risk variable is linked to the macroeconomic variables.

2.2 The choice of credit risk variable

Ultimately, the impact of the stress test has to be translated into losses for the banks. That is, the credit risk components of expected losses - the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD) - have to be mapped into observable variables. While EAD may be observed from information on the banks' loan portfolios, PD and LGD have to be estimated or proxied by observable variables that relate to credit risk. In this sub-section, we discuss the different types of credit risk variables used in practice and raise the issue of sensitivity of stress testing results to the choice of different credit risk variables. This choice is often determined by practical considerations, such as data availability at the desired level of data aggregation.

2.2.1   Credit risk variables used in practice

Several variables have been used in credit stress testing applications. We distinguish between variables based on bank accounting data, default data and model-based measures, respectively.

Bank accounting data

A bank accounting measure that may serve as a proxy for PD is the ratio of (new) *non-performing loans* to a given measure of total loans (NPL ratio). This variable has been suggested by Blaschke *et al.* (2001), among others, and used by Jakubík and Heřmánek (2008), Jakubík and Schmieder (2008), Vazquez, Tabak and Souto (2012) and Buncic and Melecky (2013). Conceptually, the NPL ratio may be a good proxy for PD, as non-performing loans are those loans for which the contractual interest or principal will likely not be collected and which are therefore technically in default. However, until 2014, there was no single definition of non-performing loans in the European Union; while non-performing loans were usually determined by a criterion such as x days overdue, the value of x typically differed across banks (x has now been set at 90 in the EU). Therefore, until recently, the NPL ratio was not entirely comparable across EU banks.

Following an increase in expected credit loss (due to a rise in PD or LGD), banks may set aside new provisions and record them as impairments on the expenditure side of their P&L, with an ultimate impact on their Tier 1 capital through lower retained earnings. Therefore, another natural

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[10] One can distinguish models where the macroeconometric model and the credit risk model are two separate entries or modules in the stress testing framework and models where the link between credit risk and macroeconomic developments is integrated into or jointly estimated with the macroeconometric model. See Ferrari *et al.* (2011) for a discussion of the implications of these differing model structures.

candidate for capturing credit risk is the ratio of (new) *loan loss provisions* (or impairments) to a given measure of the stock of total loans (LLP ratio, also referred to as the credit cost ratio). This credit risk variable is often used in stress testing applications (see Kalirai and Scheicher, 2002; Lehmann and Manz, 2006; Sorge and Virolainen, 2006; van den End, Hoeberichts and Tabbae, 2006; Głogowksi, 2008; and Gutiérrez Girault, 2008). Interestingly, the LLP ratio is not a pure measure of PD; it also entails an LGD component.[11] However, accounting rules on provisioning generally differ across jurisdictions. In addition, changes in the LLP ratio do not necessarily reflect only credit risk, but may also depend on banks' provisioning policies, which may involve, for example, income smoothing for fiscal reasons.[12] Thus, within the existing regulations, banks often have some discretion in recording new impairments.

This potential lack of comparability of loan loss provisions and, until recently, non-performing loans across EU banks implies that it may be useful to complement bank accounting measures of credit risk with more direct or strictly defined measures of borrower default.

Default data

Another proxy for PD may be found in banks' databases of borrowers' defaults; these data may be available at borrower level (as a 0/1 indicator of default), or at more aggregate levels expressed as a portfolio *default rate*. Studies that use default rates as the credit risk variable include Wong, Choi and Fong (2008), Jiménez and Mencía (2009), Simons and Rowles (2009), and Jokivuolle and Virén (2013). While the Basel II framework provides a uniform definition of default (an obligor being considered to be in default when either the bank considers that the borrowers are unlikely to meet their credit obligations in full or when they are more than 90 days overdue on any material credit obligation to the bank), it is not fully harmonised across banks. Borrowers' default data are sometimes also centralised in (central banks') credit registers, to which banks typically have to report loan-level information for each loan contract whose size exceeds a given (relatively low) threshold. These data sources therefore provide wide coverage of the banks' loan portfolios. In contrast to bank accounting data, however, these data are usually not publicly available.

As an alternative to default information, which is not always available in credit registers, information on bankruptcy filings may be used. While *bankruptcy rates* are likely to understate default - as default is not always followed by bankruptcy - they are nevertheless relatively frequently used as a credit risk dependent variable in stress testing because of the lack of publicly available data on default (see Boss, 2002; Virolainen, 2004; Misina, Tessier and Dey, 2006; Sorge and Virolainen, 2006; van den End, Hoeberichts and Tabbae, 2006; Andersen *et al.*, 2008; Bernhardsen and Syversten, 2009; and Bruneau *et al.*, 2012). In contrast to default data, information on bankruptcy filings is usually publicly available. However, bankruptcy data usually only apply to firms; therefore, they cannot provide an estimate of default rates for loans to households, for example.

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[11] In fact, van den End, Hoeberichts and Tabbae (2006) exploit this feature of the LLP ratio to separately identify the behaviour of LGD in addition to that of PD by combining data on the LLP ratio with bankruptcy rate data.

[12] See e.g., Foglia (2009).

Model-based measures

A final category of measures used as credit risk variables in stress testing consists of model-based measures. Rather than directly conducting the analysis on the basis of observed credit risk variables, these studies typically employ a combination of *market information*, such as stock returns or CDS spreads, and a (structural) portfolio credit risk model to generate estimates of banks' credit losses under adverse scenarios.

When market information is used to derive the credit risk variable, two possible approaches can be followed to link the credit risk variable to the macroeconomic variables. One approach is to first estimate the credit risk component of the market price, using macroeconomic variables as explanatory variables, and then to evaluate the credit risk component using stressed values of the macroeconomic variables (see Åsberg and Shanazarian, 2008; and Castrén, Dées and Zaher, 2010 using Moody's KMV EDFs that are extracted from stock market data using a Merton-type approach). An alternative approach, as followed by Drehmann (2005) and Pesaran *et al.* (2006), is to first estimate the relationship between the market data and the macroeconomic variables, to evaluate market prices at stressed values of the macroeconomic variables, and then to extract the credit risk variable from the stressed market price data.[13] The advantage of the market-based indicators is that they can be constructed on the basis of borrower-level data that are publicly available. However, the coverage of banks' loan portfolios that can be obtained in this approach may be limited, since market data are only available for publicly listed firms and are typically not available for SMEs and households, which may represent a large proportion of the banks' loan portfolios. Finally, movements in market prices are not necessarily related to credit risk; market price changes are also likely to reflect other factors that may be unrelated to credit risk, such as market liquidity, investors' risk aversion or general market sentiment.[14]

As an alternative to market-based credit risk information, one may consider using banks' model-based *internally estimated PDs*, which are assigned to each loan in a portfolio. In the Basel framework's internal ratings-based (IRB) approach, these estimated default probabilities are used for computing risk exposure amounts in order to determine the bank's regulatory capital requirement. As banks' internally estimated PDs are usually not publicly available, these data are rarely used in stress testing exercises (a notable exception is Düllmann and Kick, 2014). In addition, some authorities have found that different banks sometimes assign quite different PDs to the same firms (Gustin and Van Roy, 2014). Another disadvantage of banks' internally estimated default probabilities, besides their limited availability, is the fact that these PDs may often be "through-the-cycle", meaning that the PD for a borrower may be estimated as an average value over an entire economic cycle.

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[13] An interesting but unanswered question is how big the difference is between the stressed values of the credit risk variables, and hence, the results of the stress test, from these two approaches.
[14] This is not only true for stock prices, which in general may be expected to depend on all factors that affect the firm's future profitability, but also for credit default swaps (see Collin-Dufresne *et al.*, 2001; Bongaerts *et al.*, 2011; and Annaert *et al.*, 2013).

2.2.2 Sensitivity of stress testing results across different credit risk variables

As no ideal measure of credit risk seems to exist, practitioners often have to choose among different potential credit risk variables, and the ultimate choice may to a large extent be driven by practical considerations, such as data availability. It is therefore important to assess the sensitivity of stress testing results to the choice of credit risk variable.

Speed and extent of credit risk information incorporation

A general feature of the different credit risk variables that may affect the sensitivity of stress test results to the choice of credit risk variable is the speed at which and the extent to which credit risk information is reflected in the credit risk variable. In particular, one issue that has received some attention in stress testing is the backward- or forward-looking nature of the data. On the one hand, event-based data, such as non-performing loans, and default and bankruptcy data, are typically backward-looking, in that they include information only on past events. Moreover, the speed at which the evolution of credit risk is reflected in these event-based variables depends on the underlying definitions of the event, which may differ across the different variables (e.g., the number of days overdue for non-performing loans and default data, the time between actual distress and the bankruptcy filing in the case of bankruptcy rates). Credit risk variables based on loan loss provisions may, in principle, also be considered to be backward-looking, but the extent to which this is the case may depend on the bank's provisioning policy.

Model-based credit risk variables, such as those based on market information or banks' internally estimated PDs, are said to be forward-looking or *ex-ante* measures of credit risk. Model-based PDs (if based on the Basel II concept) typically reflect the probability (or expectation) of default over a future one-year horizon. Important in this respect is the potential through-the-cycle nature of the model-based credit risk variables. To the extent that they are indeed through-the-cycle, as opposed to "point-in-time", this may hamper the finding of any statistically significant relationship of the credit risk variable with macroeconomic movements.[15]

These features of the various credit risk variables may imply different (timing in the) reactions of specific credit risk variables to stressed macroeconomic variables and hence, potentially different stress testing results.

Stocks versus flows

Not only using inherently different types of credit risk variables, but also the use of different variants or transformations of particular credit risk variables may raise sensitivity issues regarding stress testing results. For instance, it has been suggested by Pain (2003), Jakubík and Heřmánek (2008), and Jakubík and Schmieder (2008), for example, to use flows of new loan loss provisions and non-performing loans, respectively, since write-offs and reversals may blur the picture of developments in credit risk obtained from looking at the outstanding stocks of these accounting variables (e.g., large write-offs may result in a decrease in the stock of LLPs and NPLs, even when the flow of new

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[15] Sorge and Virolainen (2006) observe that while accounting measures of risk are very sensitive to the business cycle, market-based indicators exhibit substantial variability both across firms and over time, but appear to be less responsive to macroeconomic or systematic risk factors.

provisions and non-performing loans has increased).[16] To the extent that an LLP or NPL ratio constructed from the stock of LLPs or NPLs, respectively, reacts differently to the macroeconomic variables than an LLP or NPL ratio based on the flow of new provisions or non-performing loans, respectively, the use of these different variants or transformations of these credit risk variables may introduce sources of divergence in stress testing results.

2.3 The choice of the level of data aggregation

Stress tests can be conducted at several levels of aggregation, implying different levels of aggregation at which the credit risk variable can be linked to the macroeconomic variables. This section considers the different levels of data aggregation at which credit risk variables can be linked to the macroeconomic environment.[17] Like the choice of the credit risk variable, the choice of the level of data aggregation at which the credit risk variable is linked to the macroeconomic variables is often determined by practical considerations, such as data availability. Again, this may raise the question of how sensitive stress testing results are when the link between the credit risk variable and the macroeconomic variables is estimated at different levels of data aggregation.

2.3.1 The levels of data aggregation used in practice

Several levels of data aggregation have been used in stress testing applications. In our discussion, we focus on four possible levels of aggregation: the borrower level, the bank level, the sectoral level and the economy-wide level.

Borrower level data

The approach using the data at the most granular level in linking the credit risk variable to macroeconomic developments can be obtained using *borrower-level* data (e.g., estimating a firm's or household's default probability). Examples of credit stress testing applications using borrower-level data include Drehman (2005), Pesaran *et al.* (2006), Andersen *et al.* (2008), Bernhardsen and Syversten (2009), Bruneau *et al.* (2012), and Düllmann and Kick (2014). The use of borrower-level data allows the sensitivity of the credit risk variable to macroeconomic variables to differ across firms or households.[18] In doing so, differences in the potential reactions of borrowers to adverse macroeconomic shocks may be revealed and a more detailed picture of the effect of macroeconomic stress on a bank's portfolio may be obtained. However, in order to fully exploit the informational advantage obtained by using borrower-level data, the practitioner conducting the

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[16] Write-offs imply the removal of a loan from the balance sheet when the loan is considered completely unrecoverable. Reversals occur on impairments that have previously been recognised in the accounts and follow events that suggest an increase in the recoverable amount of the asset (e.g., an improvement of the borrower's ability to pay). Reversals are recognised as a credit to the P&L.

[17] This need not coincide with the level of aggregation - e.g., portfolio, bank or system-wide level - at which the resilience assessment in terms of losses or capital adequacy is performed.

[18] In addition, borrower-specific characteristics (e.g., firm size or firm accounting variables, household income) can be controlled for in order to improve the predictive power of the credit risk model. A large literature exists on predicting borrowers' default/bankruptcy using micro and macro variables (see Jacobson *et al.*, 2009 and the references therein). Among the models in this literature, which may be used for stress testing as well, interesting applications on bank regulatory issues include Saurina and Trucharte (2007) on Basel II pro-cyclicality in mortgage portfolios, and Chionsini, Marcucci and Quagliariello (2010) on the treatment of small and medium enterprises in Basel II.

stress test should have knowledge of (or make assumptions about) the exact composition of the banks' portfolios. This may be problematic for top-down stress tests. Even in a bottom-up stress test, the borrower-level approach may not be feasible, in that evaluating the sensitivity of the credit risk of every individual borrower to macroeconomic stress may require substantial IT resources.

Bank level data

When data on the credit risk of individual borrowers and/or information on the banks' portfolio composition are not available, an alternative may be to use credit risk information aggregated at the level of the different banks (*bank-level* data, such as non-performing loans or impairments). Applications in the stress testing literature include Lehmann and Manz (2006), Gutiérrez Girault (2008), Głogowksi (2008), and Buncic and Melecky (2013). While linking the credit risk variable to the macroeconomic environment at this level of aggregation does not make it possible to differentiate between the effects of macroeconomic stress on the different individual firms or the different loan portfolios of the bank, it does allow for distinguishing the effects of macroeconomic stress across banks.

Sectoral data

Alternatively, *sectoral* credit risk data may be used for stress testing (see e.g., Virolainen, 2004; Sorge and Virolainen, 2006; Misina, Tessier and Dey, 2006; Jakubík and Heřmánek, 2008; Jakubík and Schmieder, 2008; Wong, Choi and Fong, 2008; Jiménez and Mencía, 2009; Simons and Rolwes, 2009; Castrén, Dées and Zaher, 2010; Breuer *et al.*, 2012; and Düllmann and Kick, 2014). In a narrow sense, sectors may refer to different corporate or industrial sectors as well as to the more general distinction between for example the corporate sector and the household sector. More broadly, a breakdown of the credit risk of exposures by for example geographical location or firm size may also be considered to be "sectoral" data. The sectoral approach enables heterogeneous treatment of banks in terms of sensitivity to macroeconomic stress, provided that information is available on the banks' exposures to different sectors. Obviously, it may also be possible to combine the sectoral approach with the previous level of aggregation, i.e., to obtain sectoral credit risk data at the level of the different banks (bank-sector observations, see Segoviano and Padilla, 2006; and Vazquez, Tabak and Souto, 2012, for example).[19]

Economy-wide data

The final level of aggregation is economy-wide. The advantage of such an aggregate approach is that economy-wide data are generally more readily available than more granular data. Applications are therefore ubiquitous, including Boss (2002), Kalirai and Schleicher (2002), Sorge and Virolainen (2006), van den End, Hoeberichts and Tabbae (2006), Åsberg and Shahnazarian (2008), Wong, Choi and Fong (2008), Simons and Rolwes (2009), Castrén, Dées and Zaher (2010) and Buncic and Melecky (2013). Modelling the aggregate behaviour of borrowers is also potentially

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[19] Similarly, combining information on different "sectors", e.g., model-based probabilities of default of different industrial sectors for different geographical locations is also an option.

less complex and more robust than the individual borrower approach.[20] Nevertheless, aggregate data potentially ignore significant variations across borrowers, sectors or banks that would be captured in a more granular approach.

2.3.2 Sensitivity of stress testing results across different levels of data aggregation

To perform stress testing, ideally we link the credit risk of each separate borrower in the banks' portfolios to the macroeconomic environment; the more granular the data level, the more differentiation in relationships between the credit risk variable and the macroeconomic environment can be taken into account in evaluating the effect of macroeconomic stress on the banks' solvency positions. For several practical reasons, such as the lack of granular credit risk data or information of the composition of banks' balance sheets, this may not be feasible and the credit risk variable must be linked to macroeconomic variables at a more aggregate level. The more aggregate approaches are obviously more efficient in both data and modelling resources.

However, an important question is whether stress testing results are sensitive to different choices of the level of data aggregation. As stated by Foglia (2009), analyses using econometric models based on aggregate data may conceal significant variation at the borrower, sector or bank level. To our knowledge, Vazquez, Tabak and Souto (2012) and Düllmann and Kick (2014) are the only studies that compare results of a credit stress test based on granular data to those obtained for more aggregate data.[21] More specifically, Vazquez, Tabak and Souto (2012) simulate the evolution of bank-level NPLs with and without exploiting a partition of credit portfolios by borrower types (i.e. consumer vs. corporates) and economic sectors. They find the presence of a data aggregation bias stemming from inadequate granularity in the credit portfolios which are subject to macro shocks; in particular, the bank-weighted average of the simulated NPLs using less granular portfolios is always lower than the simulated NPLs under the more granular portfolios. Similarly, Düllmann and Kick (2014) find a substantial information gain in using borrower-specific PDs instead of sector-level PD; higher dispersion in the relative increase in expected losses under the stress scenario found when using borrower-specific PDs illustrates that the use of more granular information allows a better differentiation between banks concerning the impact of different scenarios.

2.4 Summary

Different credit risk variables may react differently to stressed macroeconomic variables, potentially resulting in a sensitivity of stress testing results to the choice of different credit risk variables. In addition, not only using inherently different types of credit risk variables, but also the use of different variants or transformations of particular credit risk variables may raise robustness issues regarding stress testing results. Finally, the level of data aggregation at which the stress test is conducted may also result in diverging stress testing results when significant variation exists in the sensitivity to the macroeconomic environment across borrowers, sectors or banks.

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[20] Jacobson *et al.* (2008) compare the results of several models forecasting firms' default and find that models estimated on aggregate data exhibit a much higher parameter stability than those estimated at the borrower-level.
[21] Cerutti and Schmieder (2014) show that the outcome of a stress test is also affected by the level of consolidation of the balance sheet used in the exercise.

In the remainder of this paper, we empirically investigate these issues by estimating how the choice of different credit risk variables and levels of data aggregation in the credit model may impact credit stress testing results using data for the Belgian banking system.

3. Empirical approach

This section describes the empirical approach for evaluating the sensitivity of stress testing results across different credit risk variables and levels of data aggregation. We then present the variables used to estimate the credit risk model and perform the stress test.

3.1 Modelling approach

The empirical approach we follow in order to illustrate the importance of the choice of the credit risk variables and levels of data aggregation for stress testing results consists of five steps: (i) estimate a credit risk model in which a given credit risk variable at a given level of data aggregation is linked to the macroeconomic variables, (ii) based on this estimated credit risk model, simulate the distribution of the credit risk variable over a given stress testing horizon, conditional on a given evolution of the macroeconomic variables, (iii) use information on LGD and EAD to transform the simulated credit risk variable distribution into a simulated expected loss distribution at each time period in the stress testing horizon, (iv) for a given percentile of the simulated expected loss distribution, take the average level of the simulated expected loss over the stress testing horizon, and (v) subtract from this average level the expected loss of the last period before the stress testing horizon and express this difference in terms of impact on the Tier 1 capital ratio. The sensitivity of stress testing results to the choice of different credit risk variables and different levels of aggregation can then be assessed by comparing the simulated impacts on the banks' solvency positions across different credit risk variables and levels of data aggregation.

In our application, we perform step (i) by estimating the following linear equation:

$$C_t = \propto + \sum_{j=1}^{l} \beta_{t-j} C_{t-j} + \sum_{i=1}^{m} \sum_{j=0}^{l} \gamma_{i,t-j} M_{i,t-j} + \varepsilon_t \qquad (1)$$

where C_t denotes the value of the credit risk variable at time t, $M_{i,t}$ the value of macroeconomic variable i at time t, m is the number of macroeconomic variables included in the model, l is the number of lags of the independent variables and ε_t is the value of the error term at time t.[22] This type of autoregressive distributed lag (ADL) credit risk model is frequently used by the IMF in its FSAP (see e.g. IMF, 2011, where it is used to forecast the LLP ratio) and by many central banks as part of their top-down stress test framework (see e.g. ECB, 2013 and 2017). Several academic papers have also used it for forecasting credit risk variables (see Virolainen, 2004, for the bankruptcy rate or Buncic and Melecky, 2013, for the NPL ratio).

In step (ii) we take 100,000 random draws of ε_t from the normal distribution for each period in the stress testing horizon. On the basis of the estimated equation (1) and changes in the

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[22] Within this framework, one could also have assumed that the macroeconomic variables follow a vector autoregressive (VAR) system.

macroeconomic variables over the stress testing horizon, this results in 100,000 predictions of C_t for each period in this horizon[23]. Hence, for each period in the stress testing horizon, a distribution for the simulated credit risk variable conditional on movements in the macroeconomic variables is obtained. Using information on LGD and EAD, simulated conditional expected loss distributions are consequently calculated in step (iii) on the basis of the formula EL=PD*LGD*EAD.

The advantage of working with expected loss distributions rather than a point estimate for expected losses in each time period over the stress testing horizon is that a distribution enables us to not only look at the mean predicted expected loss but also at higher percentiles of the distribution, which is useful to account for the presence of model uncertainty in the equations linking the credit risk variables and the macroeconomic variables.[24] Therefore, in step (iv), we consider both the 50th percentile and the 75th percentile of the simulated expected loss distributions. This enables an assessment of the sensitivity to modelling choices of the stress testing results for not just the median of simulated expected losses distributions in each period, but also for more severe predictions of simulated expected losses.

Finally, in step (v), we take the difference between the stressed expected loss level obtained in step (iv) for a given percentile p of the expected loss distribution and the expected loss of the last period before the stress testing horizon, resulting in an average change in the level of expected losses over the stress testing horizon compared to the level in normal times for the given percentile p of the expected loss distribution. Assuming that this change in the level of expected losses is entirely deducted from Tier 1 capital, the average change is expressed in terms of impact on the Tier 1 capital ratio as follows:

$$Tier\ \mathbf{1}\ impact(p) = \frac{\Delta EL(p)}{REA}$$

(2)

where $\Delta EL(p)$ denotes the average change in expected losses for the given percentile p of the expected loss distribution and REA are risk exposure amounts.[25]

3.2 Data

In our stress testing application, we use quarterly data for the Belgian banking system on the different credit risk variables and macroeconomic variables. The estimation of the credit risk model is performed over the sample 1995Q1-2013Q4 and the stress testing horizon spans the period 2014Q1-2016Q4. In the following sub-sections, we present these data in more detail. For a description of each of the variables used in the credit risk model, see Table A1 in the appendix.

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[23] The model is solved with stochastic mean and confidence bounds.

[24] Model uncertainty refers here to the fact that there is a risk that the chosen credit risk model underestimates the risk parameter response and as a consequence overestimates the loss absorption capacity of the banks, even if its results may be sound and look acceptable from an economic and econometric viewpoint. The use of a higher percentile or of alternative stress testing techniques, such as the Bayesian model averaging methodology promoted by Gross and Población (2015), may help to mitigate that risk. In this paper, the choice of the 75th percentile is arbitrary (the selection of higher percentiles would make no difference to our main message).

[25] Due to a lack of data on banks' internal credit risk models, we abstain from simulating the increase in risk exposure amounts induced by the change in the credit risk variables. The sensitivity of Belgian banks' REA to changes in credit risk can be found in the published results of the 2014 EBA stress test.

3.2.1 The credit risk variables

In our analysis, we consider two sets of credit risk variables: one for assessing the sensitivity of stress testing results to the choice of the credit risk variable, and one for the choice of the level of data aggregation.

The choice of credit risk variable

As discussed in Section 2.2, three categories of credit risk variables have been used in the stress testing literature: bank accounting data, default data and model-based measures. In our application, we assess the sensitivity of stress testing results across four variables measuring the credit risk of Belgian banks. The first three belong to the category of *bank accounting data* and the last one to the category of *default data*. In particular, we consider the stock of non-performing loans as a percentage of total loans (NPL ratio) of Belgian banks, the stock of loan loss provisions as a percentage of total loans (LLP ratio) of Belgian banks, the flow of loan loss provisions as a percentage of total loans (FLLP ratio) of Belgian banks, and the bankruptcy rate among Belgian firms (BR). The NPL, LLP and FLLP ratios were obtained from data in the FINREP supervisory reporting scheme while the bankruptcy rate was obtained from data on bankruptcy filings and the NBB's central corporate credit register. Each of these data sources is confidential.

While credit risk variables are available at the bank level, we nevertheless perform our analysis for a representative bank by aggregating information from individual banks incorporated under Belgian law (i.e. solo data). While working at the aggregate instead of individual bank level is essentially for simplicity and illustrative purposes, it has the additional benefit of smoothing the series for the NPL, LLP and FLLP ratios. As the Belgian accounting and regulatory framework provides flexibility to banks in the way they recognise their loan losses (see Arbak, 2016), there is room for considerable bank-specific variability. Thus, our choice of working with aggregate data also allows us to discount this source of variability and focus only on the variability that may be driven by choice of credit risk variable and the level of data aggregation.

It is worth mentioning that while the NPL, LLP and FLLP ratios capture the credit risk of loans to all types of counterparties irrespective of their geographical location (domestic and foreign), bankruptcy rates only reflect the credit risk originating from loans to Belgian firms. Even though this difference in scope of coverage is mitigated by the fact that we work with solo data, it may, together with the reasons mentioned in the previous sections, translate into differences in expected losses once the different credit risk variables are stressed, depending on how each variable evolves over time and is linked to macroeconomic fluctuations.

Figure 1 shows that the four credit risk variables follow a relatively similar pattern over the sample period 1995Q1-2013Q4, i.e. a decrease prior to the 2007-2008 financial crisis followed by an increase afterwards. Regarding the level of the variables, the values of the flow variables (FLLP ratio and BR) are below those of the stock variables (NPL and LLP ratios) because they only account for new (annualised) provisions and bankruptcies in a given quarter. In addition, the bankruptcy rate is somewhat higher than the FLLP ratio because the credit risk originating from loans to Belgian firms has been traditionally higher than the credit risk of loans to all types of counterparties, irrespective of their geographical location.

FIGURE 1. Trend in credit risk variables, 1995Q1-2013Q4 (all variables in %).
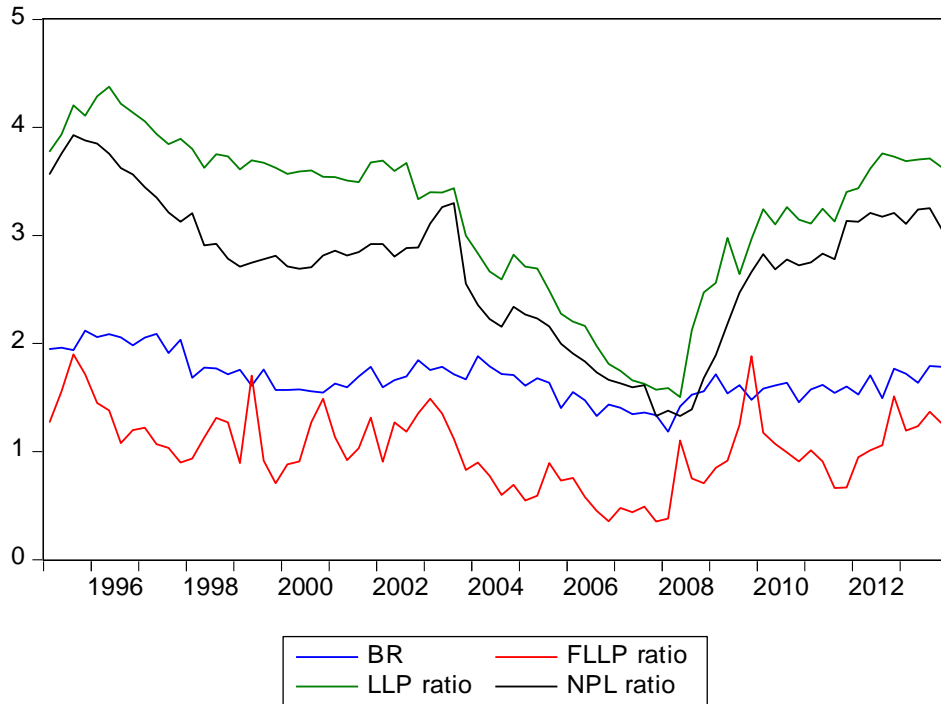
Note: (1) The NPL and LLP ratios are stock variables; the quarterly observations correspond to yearly credit risk parameters. The FLLP ratio and BR, on the other hand, are flow variables. That is, they represent the new impairments and bankruptcy filings, respectively, recorded every quarter. Therefore, the FLLP and BR series in Figure 1 and the subsequent analysis are annualised (sum over the last four quarters). (2) The two variables based on loan loss provisions entail an LGD component, whereas BR and the NPL ratio are proxies for PD only. Therefore, the values of the LLP and FLLP ratios are divided by an assumed LGD of 0.45 in order to serve as a proxy for PD (in practice, LGD values differ e.g. across types of loans and vary over time). All variables are seasonally adjusted. In a few cases, we have corrected for outliers as further data investigation showed that they were purely driven by idiosyncratic factors.

The similar pattern of the different variables over the sample period is confirmed in Table 1, which indicates that the four variables are highly correlated. This is not only true for the mutual relationships among the different bank accounting data, but also, and despite their different coverage, for the relationship between the bankruptcy rate and the different accounting variables.

TABLE 1. Correlation among different credit risk variables, 1995Q1-2013Q4.

|	BR	FLLP ratio	LLP ratio	NPL ratio
BR	1.00			
FLLP ratio	0.56	1.00		
LLP ratio	0.76	0.70	1.00	
NPL ratio	0.77	0.72	0.95	1.00

The choice of level of data aggregation

Besides the choice of credit risk variable, we have explained in Section 2.3 that the level at which credit risk is aggregated and linked to the macroeconomic variables is an additional important modelling decision to be made by the stress test practitioner. To test the extent to which stress

testing results may vary across different levels of aggregation, we use the data on bankruptcy rates and compare the results obtained at the economy-wide data level with those obtained from using a credit risk model based on a lower level of data aggregation (sectoral). In particular, we consider the four following "sectors": small manufacturing firms, large and medium-sized manufacturing firms, small non-manufacturing firms, and large and medium-sized non-manufacturing firms. Just before the start of the stress test simulation period (2013Q4), these four sectors accounted respectively for 6%, 1%, 88%, and 5% of the total population of Belgian firms.[26] In addition, we also consider two intermediate levels of data aggregation: manufacturing versus non-manufacturing firms (industrial sectors), and large and medium-sized firms versus small firms (firm size).

Figure 2 shows the trend in the (annualised) quarterly bankruptcy rate at the economy-wide level and across the different levels of data aggregation by sector and firm size. Table 2 below reports the correlations among these variables.

FIGURE 2. Trend in the bankruptcy rate for different levels of data aggregation, 1995Q1-2013Q4 (in %).

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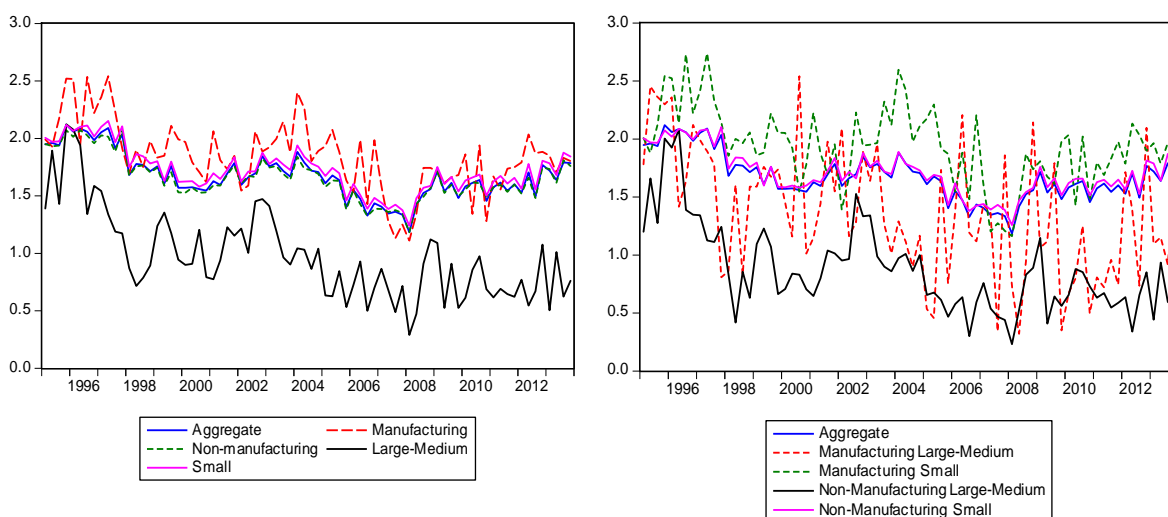
[26] Each firm is classified in either the manufacturing or non-manufacturing sector according to its NACE code and in each size category according to its total sales and total assets. While manufacturing firms represent less than 10% of the total number of firms, they are usually larger in size than non-manufacturing firms.

TABLE 2. Correlation among bankruptcy rates for different levels of data aggregation, 1995Q1-2013Q4.

	economy-wide	manuf.	non-manuf.	medium/large	small	medium/large manuf.	small manuf.	medium/large non-manuf.	small non-manuf.
economy-wide	1.00								
manuf.	0.79	1.00							
non-manuf.	0.99	0.74	1.00						
medium/large	0.77	0.61	0.76	1.00					
small	0.99	0.79	0.99	0.72	1.00				
medium/large manuf.	0.45	0.45	0.43	0.70	0.41	1.00			
small manuf.	0.74	0.96	0.69	0.47	0.75	0.19	1.00		
medium/large non-manuf.	0.78	0.59	0.78	0.96	0.73	0.49	0.51	1.00	
small non-manuf.	0.99	0.73	0.99	0.72	0.99	0.42	0.69	0.73	1.00

Both the figure and the table reflect the sectoral composition of the Belgian firms: the economy-wide pattern of bankruptcy rates closely follows that for small non-manufacturing firms, which represent almost 90% of the sample. The correlation between bankruptcy rates at the economy-wide level and bankruptcy rates of large and medium-sized manufacturing firms is markedly lower. Therefore, when linking the economy-wide bankruptcy rate to the macroeconomic variables, it is mainly the sensitivity of small non-manufacturing firms to the macroeconomic environment that is reflected in the estimates. This may have a strong impact on stress testing results when large manufacturing firms behave quite differently over the cycle and banks have substantial exposures to the latter.
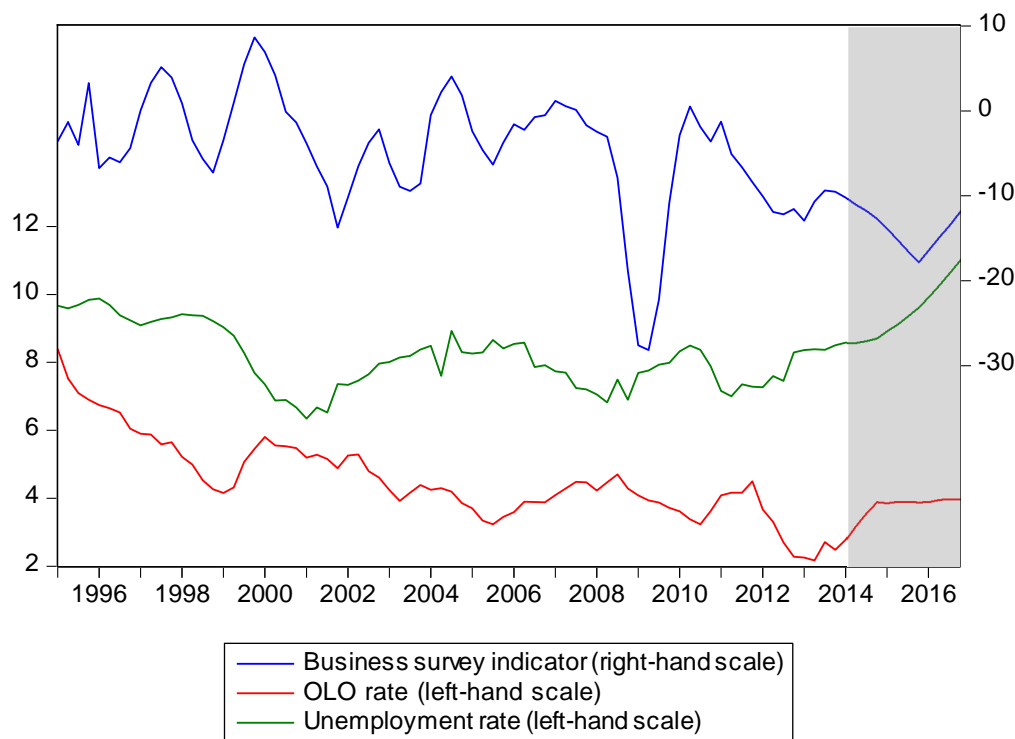
3.2.2 Macroeconomic variables and the macroeconomic stress scenario

Finally, we briefly discuss the three macroeconomic variables that we use in our application: Belgium's business survey indicator (as a proxy for GDP growth),[27] Belgium's unemployment rate (to cover the income and demand channel) and the 10-year yield on Belgian government bonds, the so-called OLO rate (to cover debt servicing costs). Figure 3 shows the actual change in these three variables over the period 1995Q1-2013Q4 as well as their trend under the adverse macroeconomic scenario of the 2014 EBA stress test (as indicated by the grey shaded area). It is

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27 The business survey indicator, which is compiled on the basis of the responses to the business survey which the NBB conducts each month among firms in Belgium, captures cyclical movements in economic activity. It is highly correlated with GDP growth while offering a broader view of economic trends and comprising information on variables such as expectations (see De Greef and Van Nieuwenhuyze, 2009). Notwithstanding the strong correlation, the significance of the business survey indicator is higher than that of GDP growth in our credit risk model estimations. Therefore it is used as a proxy for GDP growth in this paper.

immediately apparent that there is quite some variation in the macroeconomic variables, which was to be expected given that we cover more than a complete economic cycle.

FIGURE 3. Trend in macroeconomic variables, 1995Q1-2016Q4
(all variables in % except the business survey indicator, in points).

While the actual change in macroeconomic variables over 1995Q1-2013Q4 (available from NBB.Stat) is used in the credit risk model estimation, data over the period 2014Q1-2016Q4 obtained from the 2014 EBA stress test's adverse macroeconomic scenario (see ESRB, 2014) are considered in our stress testing application. Consistent with the overall narrative of the 2014 EBA adverse macroeconomic scenario, the business survey indicator falls before partly recovering, the unemployment rate is rising and long-term interest rates are going up before flattening out in Belgium over the period 2014Q1-2016Q4.

4. Results

As explained in the previous section, we first estimate equation (1) for the different credit risk variables using quarterly data over the sample period 1995Q1-2013Q4. For each credit risk variable, we then use the estimated credit risk model to simulate the stressed distribution of the selected credit risk variable over the stress testing horizon, using changes in the macroeconomic variables under the 2014 EBA adverse scenario over the stress testing horizon 2014Q1-2016Q4 as the stress scenario.[28] We then compute the average expected loss over the stress testing horizon on the basis of the average value of the credit risk variable over this period at the 50th and 75th

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[28] In order to ensure the reliability of the starting values for risk parameters in the stress test, we consider the average of each credit risk variable over the four quarters of 2013 as the starting point for our simulations.

percentile of the simulated stressed credit risk distributions, respectively. This stressed expected loss figure is finally expressed in terms of the impact on the Tier 1 capital ratio.

Given that our results are dependent on the specific macroeconomic scenario chosen, they should only be interpreted as an illustration of the potential importance of modelling decisions in stress testing applications.

4.1 Estimation results of the credit risk models

Before turning to the results on the sensitivity of the stress testing results to the choice of different credit risk variables and levels of data aggregation, we first discuss the estimation results of the ADL model (equation (1) in Section 3.1). Following the results of a unit root test (not reported here), all dependent (except the FLLP ratio in Table 3) and independent (except the business survey indicator) variables are taken in first differences to make them stationary.[29]

For each credit risk variable, we test several specifications of the model to select the number of lags for the independent variables. Given the limited number of observations in our time series, we need to trade off the loss in terms of degrees of freedom by adding more lags to increase the significance. While the best specification for equation (1) on the basis of model fit criteria may differ across the credit risk variables and levels of data aggregation, respectively, for reasons of comparability we estimate the same model for each of the credit risk variables and each level of data aggregation, respectively. In addition, within each regression, for simplicity, we impose the same number of lags for each independent variable. According to the Schwarz Information Criterion, including one lag of each independent variable in equation (1) most frequently turns out to be the preferred specification, both across the different credit risk variables and the levels of data aggregation. We therefore use this specification to estimate the credit risk model over the period 1995Q1-2013Q4 and to perform a stress testing exercise for the period 2014Q1-2016Q4.

The results of this specification of the credit risk model are shown in Table 3 for the different credit risk variables. Overall, the business survey indicator emerges as a statistically significant and consistent predictor of all four credit risk variables. Adding up its contemporaneous and lagged effects, we find that, all other things being equal, an improvement in the business survey indicator decreases the NPL ratio, the LLP ratio, the FLLP ratio and the bankruptcy rate, as we would expect. This result is also in line with the literature referred to in Section 3.1, which finds a negative association between GDP growth (for which the business survey indicator used in this paper serves as a leading indicator) and different credit risk variables. Other macroeconomic variables shown in Table 3 have generally a lower statistical significance. We nevertheless find that the OLO rate has some statistically significant impact on the FLLP ratio and BR, but in opposite ways: whereas a decrease in the OLO rate decreases BR, it increases the FLLP ratio. One possible explanation for the latter result may be that, especially since the 2007/2008 financial crisis, lower long-term interest rates have become associated with lower economic growth, and thus higher flows of loan loss provisions. Given the high percentage of long-term fixed loans on their balance

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[29] Even though the null hypothesis of a unit root cannot be rejected for most series, we also estimated equation (1) in levels as a robustness check. The significance level of all explanatory variables remained unchanged. We also experimented with year-on-year (instead of quarter-on quarter) changes. Here again the results did not change.

sheets, Belgian banks are more likely to be sensitive to changes in the economic cycle than to changes in interest rates per se. Finally, the coefficient of the lagged dependent variable in Table 3 shows some interesting findings with respect to the persistence effect of the different credit risk variables as it is more significant for the (annualised) flow variables (FLLP ratio and BR) than for the stock variables (NPL and LLP ratios).

TABLE 3. Results of the credit risk models: different credit risk variables.

	NPL ratio	LLP ratio	FLLP ratio	BR
Credit risk var. (t-1)	0.154 (0.122)	-0.161 (0.127)	0.577*** (0.086)	-0.546*** (0.100)
Bus. surv. indic. (t)	-0.015*** (0.005)	-0.009*** (0.003)	0.001 (0.001)	-0.003*** (0.001)
Bus. surv. indic. (t-1)	0.009** (0.004)	0.006*** (0.002)	-0.002** (0.001)	0.002*** (0.001)
UNEMP (t)	-0.053 (0.056)	0.003 (0.028)	-0.006 (0.010)	0.013 (0.009)
UNEMP (t-1)	0.028 (0.056)	0.031 (0.028)	-0.010 (0.010)	-0.004 (0.009)
OLO (t)	0.009 (0.067)	0.008 (0.034)	-0.028** (0.012)	0.019* (0.011)
OLO (t-1)	0.016 (0.065)	0.032 (0.032)	-0.024** (0.012)	-0.001 (0.011)
Constant	-0.035 (0.023)	-0.012 (0.011)	0.040*** (0.010)	-0.003 (0.004)
Observations	74	74	74	74
Adjusted R-squared	0.16	0.13	0.55	0.37

Sample period: 1995Q1-2013Q4. All variables in first differences except the FLLP ratio and the business survey indicator. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. Standard errors are in brackets.

The results for the different levels of data aggregation in Table 4 show that all three macroeconomic variables have a (marginally) significant impact on the bankruptcy rate of the small non-manufacturing sector, which accounts for almost 90% of the total number of Belgian firms. For other sectors, macroeconomic variables display a lower level of significance with the exception of the business survey indicator for large and medium-sized non-manufacturing firms. Again, an interesting variation in persistence effects is observed: whereas bankruptcy rates in the manufacturing sector exhibit positive persistence effects, those in the non-manufacturing sector have negative persistence, which dominates at the aggregate level.

Interestingly, other contributions in the field of stress testing which rely on an ADL framework also find a strong persistence of the credit risk variables. This is the case for instance in IMF (2011), where an ADL model is applied to the LLP ratio of a sample of small and medium-sized German banks, and in Buncic and Melecky (2013), where a model of this kind is used to forecast the NPL ratio in a panel of 54 countries. In order to check that the persistence effect does not take over some of the explanatory power of other explanatory variables, we first removed the lagged credit risk variable from our credit risk model following a suggestion made by the IMF (2015). However, we found the statistical significance of the macroeconomic explanatory variables to be unchanged across the different credit risk variables and levels of data aggregation. Second, and while a credit risk model including one lag of each independent variable often turned out to be the preferred specification according to the Schwarz Information Criterion, we added different numbers of lags to each credit risk variable. Here again, the level of significance of the macroeconomic variables barely changed (see also Section 4.3 for a discussion of the impact of this sensitivity check on our main result).

TABLE 4. Results of the bankruptcy rate (BR) model: different levels of data aggregation.

	economy-wide	small manuf.	medium/large manuf.	small non-manuf.	medium/large non-manuf.
BR (t-1)	-0.546*** (0.100)	0.523*** (0.104)	0.241** (0.120)	-0.579*** (0.097)	-0.390*** (0.115)
Bus. surv. indic. (t)	-0.003*** (0.001)	-0.000 (0.002)	-0.004 (0.004)	-0.003*** (0.001)	-0.003 (0.002)
Bus. surv. indic. (t-1)	0.002*** (0.001)	-0.001 (0.002)	0.002 (0.004)	0.002*** (0.001)	0.003** (0.002)
UNEMP (t)	0.013 (0.009)	-0.027 (0.028)	0.007 (0.053)	0.016* (0.009)	0.033 (0.024)
UNEMP (t-1)	-0.004 (0.009)	-0.035 (0.027)	-0.004 (0.052)	-0.002 (0.009)	0.013 (0.024)
OLO (t)	0.019* (0.011)	-0.018 (0.034)	-0.045 (0.063)	0.020* (0.011)	0.002 (0.030)
OLO (t-1)	-0.001 (0.011)	-0.043 (0.032)	-0.023 (0.063)	0.001 (0.011)	0.015 (0.028)
Constant	-0.003 (0.004)	0.219*** (0.051)	0.244*** (0.043)	-0.002 (0.004)	-0.001 (0.009)
Observations	74	74	74	74	74
Adjusted R-squared	0.37	0.30	0.01	0.41	0.10

Sample period: 1995Q1-2013Q4. All variables in first differences except the business survey indicator. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. Standard errors are in brackets.

4.2 The sensitivity of stress testing results

As explained in Section 3.1, we express the results of our stress testing exercise for the different credit risk variables and for the different levels of aggregation in terms of expected losses and the impact on the banks' Tier 1 ratio. In particular, using information on LGD and EAD, the estimated changes in the credit risk variable can be converted into changes in expected losses on the basis of the formula EL=PD*LGD*EAD. Adding information on REA, the impact on Tier 1 capital can be calculated using equation (2) in Section 3.1.

We make the following assumptions for the LGD, EAD and REA values. As for LGD, we assume a fixed value of 0.45 throughout the analysis. For both EAD and REA, we consider two possible values. First, we use the Belgian banks' total EAD (€1,001bn) and REA (€351bn) at the start of the stress test simulation period (2013Q4) and express our results in terms of impact on *total* Tier 1 ratio.[30] Since, bankruptcy rates only reflect the credit risk originating from loans to Belgian firms, unlike the NPL, LLP and FLLP ratios, which reflect the credit risk of all types of counterparties, we replicate the same calculations using data on Belgian banks' corporate EAD (€271bn) and REA on the corporate portfolio (€142bn) in order to express our results in terms of impact on *corporate* Tier 1 ratio. Table 5 shows the results of our exercise.

4.2.1 The choice of credit risk variable

Panel A of Table 5 reports the impact of our stress scenario on the banks' total Tier 1 capital ratio for the different credit risk variables. Using data on total EAD and REA, we find that the effect of the stress scenario decreases the banks' total Tier 1 ratio by an average of 0.56pp for the 50th percentile of the expected loss distribution and by 1.70pp on average when focusing on the 75th

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[30] Given that our credit risk variables only capture the credit risk of loans, we need to assume that the PD of loans and the PD of non-loan exposures (debt securities) are similar when multiplying our credit risk variables by the EAD.

percentile. Especially in the case where the third quartile of the expected loss distribution is considered, there is substantial variation across the different credit risk variables, ranging from 0.08pp when using the FLLP ratio to -2.93pp when using the LLP ratio as a credit risk variable. That is, despite the relatively high correlations across the different credit risk variables, using different variables in a stress testing exercise may lead to substantial differences in the stress testing results.

The results for the FLLP ratio, which show a modest increase in banks' total Tier 1 ratio at the 50th (0.28pp) and 75th (0.08pp) percentiles of the expected loss distribution, are interesting for two reasons at least. First, they demonstrate that a stress test exercise may lead to overoptimistic (and sometimes implausible) forecasts depending on the credit risk variable chosen, even though the results of the corresponding credit risk model were satisfactory and the macroeconomic scenario underpinning the stress test was judged severe enough.[31] This precisely illustrates the type of model uncertainty (or risk) referred to in Section 3.1. Second, the results for the FLLP ratio show that the use of higher percentiles of the expected loss distribution can help to mitigate this uncertainty, the change in banks' total Tier 1 ratio being lower and closer to zero at the 75th percentile than at the 50th percentile.

The impacts on the banks' corporate Tier 1 ratio calculated on the basis of corporate EAD and REA are simply a rescaling of the impacts on the banks' total Tier 1 ratio. In particular, they amount to $\frac{corporate\ EAD/corporate\ REA}{total\ EAD/total\ REA}$ = **67.1%** of the results based on total EAD and REAs. The reason for this is that, when considering only the corporate portfolio, REAs are relatively more important than EAD since corporates generally receive higher risk weights than the other counterparts in the total portfolio. Hence, the impact of the stress scenario on the banks' corporate Tier 1 ratio amounts to an average decrease of 0.38pp for the 50th percentile of the expected loss distribution and of 1.14pp for the 75th percentile. The corresponding ranges of the impacts on the banks' corporate Tier 1 ratio, which are reduced by the same factor, amount to 1.03pp and 2.02pp at the 50th and the 75th percentiles respectively, which is still important, depending on the starting level of the banks' solvency position.

Given the substantial variations that exist between the ranges of impacts observed at the 50th and the 75th percentiles of the expected loss distribution, the question arises as to whether one should consider the former or the latter threshold to gauge the importance of the choice of credit risk variable. There are two reasons supporting use of the upper quartile rather than the median of the simulated expected loss distribution. First, as explained above, the use of 75th percentile is helpful to mitigate model uncertainty. Second, the results of the 2014 EBA stress test, from which our stress testing application has borrowed the adverse macroeconomic scenario, showed that the weighted average impact of credit risk through P&L on Belgian banks' total Tier 1 ratio amounted to -2.35pp in the adverse scenario. In other words, the average impact observed in a real-life stress test exercise was closer to the average impact reported in Panel A of Table 5 for the 75th percentile of the expected loss distribution (-1.70pp) than for the 50th percentile (-0.56pp).

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[31] In the case of the FLLP ratio, the increase in banks' total Tier 1 ratio is due to the negative relationship found in the credit risk model between changes in this variable and changes in the OLO rate, the latter increasing strongly in the first year of the EBA adverse macroeconomic scenario (see Figure 3).

4.2.2 The choice of level of data aggregation

The impact of our stress scenario on the banks' Tier 1 capital ratio for the different levels of data aggregation is presented in Panel B of Table 5. In particular, we show the results for the stress test conducted at the economy-wide level, two intermediate levels (based on industrial sectors and firm size portfolios, respectively) and a disaggregate level (based on sector-size portfolio division) using BR as the credit risk variable. As these different levels of data aggregation are only analysed for the bankruptcy rate, we only calculate the impact of the stress scenario on banks' corporate Tier 1 ratio.[32]

We find that the effect of the stress scenario reduces the banks' corporate Tier 1 ratio by 1.38pp on average for the 50th percentile of the expected loss distribution and 2.54pp when focusing on the 75th percentile. As for the different credit risk variables, we find substantial variation across the different levels of data aggregation of the expected loss distribution ranging, in the case of the third quartile, from -1.10pp when considering the economy-wide level to -3.86pp when working with the most disaggregate level.

TABLE 5. The sensitivity of stress testing results.

	BR	FLLP ratio	LLP ratio	NPL ratio	Average	**Range**
A. Impact on Tier 1 capital ratio of different credit risk variables						
			Total EAD and REA			
50th percentile	-0.48pp	0.28pp	-1.25pp	-0.80pp	-0.56pp	**1.53pp**
75th percentile	-1.64pp	0.08pp	-2.93pp	-2.31pp	-1.70pp	**3.01pp**
			Corporate EAD and REA			
50th percentile	-0.33pp	0.19pp	-0.84pp	-0.54pp	-0.38pp	**1.03pp**
75th percentile	-1.10pp	0.05pp	-1.97pp	-1.55pp	-1.14pp	**2.02pp**

	Economy-wide	Industrial sector	Firm size	Sector and Size	Average	**Range**
B. Impact on Tier 1 capital ratio for different levels of data aggregation using BR as the credit risk variable						
			Corporate EAD and REA			
50th percentile	-0.33pp	-2.63pp	-0.31pp	-2.26pp	-1.38pp	**2.32pp**
75th percentile	-1.10pp	-3.58pp	-1.63pp	-3.86pp	-2.54pp	**2.76pp**

4.3 Sensitivity checks

The above stress testing results were obtained on the basis of the specification of the credit risk model with one lag for each independent variable. Since this was not always the preferred model specification, we report in Table 6 the maximum difference in the final impact on Tier 1 capital ratio across the different credit risk variables and different levels of data aggregation, respectively, for

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[32] The results based on total EAD and REAs could be obtained by dividing the results based on total EAD and REAs by 0.671.

different numbers of lags of the independent variables included in the credit risk model. The figures in the first column in Table 6 coincide with those reported in the last column of Table 5.

Panel A of Table 6 shows that for both the 50th and the 75th percentile of the expected loss distribution, there is always at least one alternative credit risk model for which the range of impacts on the Tier 1 ratio across the different credit risk variables increases compared to our base specification with one lag. In particular, the difference between the largest and the smallest impact on the total Tier 1 ratio across the different credit risk variables is highest when four lags are included in the credit risk model: 2.52pp at the 50th percentile and 3.83pp for the 75th percentile (1.69pp and 2.57pp when corporate EAD and REAs are considered). In other words, our finding of substantial variation in stress testing results when using different credit risk variables is even further strengthened when some of the alternative model specifications are used. The findings with respect to the levels of data aggregation in Panel B of Table 6 further confirm the result of the benchmark specification with 1 lag.

TABLE 6. Sensitivity checks on the range of the impacts on Tier 1 capital ratio.

	1 lag	2 lags	3 lags	4 lags
A. Range of impacts on Tier 1 capital ratio across different credit risk variables				
Total EAD and REA				
50th percentile	1.53pp	1.51pp	1.80pp	2.52pp
75th percentile	3.01pp	2.96pp	3.29pp	3.83pp
Corporate EAD and REA				
50th percentile	1.03pp	1.02pp	1.21pp	1.69pp
75th percentile	2.02pp	1.99pp	2.21pp	2.57pp
B. Range of impacts on Tier 1 capital ratio across different levels of data aggregation				
Corporate EAD and REA				
50th percentile	2.32pp	2.49pp	2.53pp	2.65pp
75th percentile	2.76pp	2.77pp	2.55pp	2.86pp

5. Conclusion

This paper has assessed the sensitivity of stress testing results to the choice of credit risk variable and level of data aggregation at which the stress test is conducted. Both choices are in fact often determined by practical considerations, such as data availability. Using data for the Belgian banking system, we find that the impact of a stress test on banks' total and corporate Tier 1 ratios can differ substantially depending on the credit risk variable and the level of data aggregation considered.

While the economic relevance of these differences of course depends on the banks' initial solvency position, the implication of this analysis is that there is a need to better harmonise the way stress tests are conducted across institutions and supervisors in order to enhance comparability, especially if solvency stress tests are going to be used as a supervisory tool (e.g. for Pillar 2

decisions via the SREP) or to set regulatory requirements (e.g. for systemically important banks). Given that there is no credit risk variable or level of data aggregation which dominates the others from a theoretical point of view, it appears more important to promote the consistent use of a given definition across banks and supervisors rather than to settle on a particular concept. This is certainly relevant in the context of the EU-wide stress tests, where institutions often use different credit risk variables and levels of data aggregation to estimate the impact of the commonly agreed stress test methodology and macroeconomic scenario on their capital while supervisory authorities rely on their own in-house models to quality assure and validate banks' projections. More generally, our results also highlight the need to improve the availability and quality of the data to be used for stress testing purposes.

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Appendix

TABLE A1. Description of variables used in the credit risk model.

Variable	Definition
NPL ratio	Stock of non-performing loans / Total loans (%)
LLP ratio	Stock of impairments / Total loans (%)
FLLP ratio	Flow of new impairments (net of reversal) / Total loans (%)
BR	Bankruptcy rate = number of filings for liquidation type bankruptcy / number of companies in existence at end of previous quarter (%)
Business survey indicator	National Bank of Belgium's overall business survey indicator (points)
UNEMP	Unemployment rate (%)
OLO	10-year interest rate on Belgium government bonds (OLO rate) (%)

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