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Measuring the impact of a bank failure on the real economy: an EU-wide analytical framework

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Abstract

The crisis management framework for banks in the European Union (EU) requires the resolution authorities to identify the existence of a public interest to resolve an ailing bank, rather than to open normal insolvency proceedings (NIPs). The Public Interest Assessment (PIA) determines whether resolution objectives, including the safeguard of financial stability, can be better preserved using resolution tools than NIPs .This paper provides a contribution to the ongoing discussion on the implementation of the PIA, by presenting an analytical framework to quantify the potential impact on the real economy stemming from a bank's failure under NIPs through the interruption of the lending activity ("credit channel"). The framework is harmonized across the jurisdictions belonging to the Banking Union and aims to improve the quantitative leg of the PIA, to be coupled with qualitative elements. In a first step, we quantify the potential credit shortfall faced by firms and households due to the abrupt closure of a bank. In a second step, the impact of the credit shortfall on real outcomes is estimated via a FAVAR model and via a micro-econometric model. Reference values are provided to assess the relevance of the estimated outcomes. The illustrative results show that such a harmonized approach can be applied across the Banking Union and to banks of heterogeneous size. In case of mid-sized banks, this common analytical framework could reduce the uncertainty regarding the extent to which the failure of the institution could have a negative impact to the real economy if the lending activity is interrupted as possibly the case under NIPs.

JEL classifications: E58, G01, G21, G28.
Keywords: bank resolution; bank insolvency; EU crisis management framework; public interest assessment, bank lending

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1. Introduction

The regulatory framework of the Banking Union, notably through the Bank Recovery and Resolution Directive (BRRD) and the Single Resolution Mechanism Regulation (SRMR), requires resolution authorities to identify the existence of a public interest to resolve an ailing bank, rather than using the normal insolvency proceedings (NIPs) available in each EU jurisdiction. The Public Interest Assessment (PIA) determines whether a resolution action is necessary for the achievement of one or more of the five BRRD resolution objectives, compared to the outcome under NIP.[1]

Over recent years, a number of features of the existing PIA framework have been subject to academic and policy debate with the objective to refine its implementation.[2] This paper contributes to this discussion in the attempt to address some of the challenges of the PIA framework. We put forward an analytical methodology, harmonized across the jurisdictions belonging to the Banking Union, to assess the impact on real economy stemming from a bank failure under NIPs. This methodology entails a sequence of steps that allow us to derive a quantitative estimation of outcomes on the real economy following the interruption of the lending activity of a credit institution, what we label as the "credit channel" of a bank failure to the real economy. The underlying intuition is that the more severe the impact on real economy of using NIPs, the stronger is the case for a positive PIA. A first approximation of the real economy effects of the simultaneous failure of several banks comes from adding up the results of the methodology for individual institutions[3]. The topic is currently in the spotlight as spillovers of the Covid-related downturn to the financial sector and back to the real economy, including through the "credit channel", cannot be excluded.

In a first step, the potential credit shortfall hitting firms and households due to the abrupt closure of one or several banks is quantified. In a second step, the impact of the firm credit shortfall on real variables is estimated both via a Factor-Augmented Vector Autoregression (FAVAR) model inspired by Budnik et al. (2019) and via a micro-econometric model inspired by Greenstone et al. (2019). Once the economic impacts of a specific bank failure are estimated, reference values (benchmarks) based on historical time series are provided to assess the relevance of the estimated outcomes.

This harmonised framework aims at improving the financial stability assessment of the PIA in its quantitative leg, which is to be coupled with qualitative elements. It is also a tangible step forward to operationalise the current legislation, which envisages that implications on the real economy

[1] Article 14 and 18(5) SRMR; Article 31 32(5) BRRD. See "Public Interest Assessment: SRB Approach", at https://srb.europa.eu/sites/srbsite/files/2019-06-28_draft_pia_paper_v12.pdf.

[2] These debated features include the following elements, among others. First, the possible consideration of system-wide events in the context of assessing the financial stability objective. Second, the need to better specify the approach to the protection of covered deposits, by assessing the operational capacity of deposit guarantee schemes (DGSs) to timely process the reimbursements in liquidation and financial stability implications stemming from the funding of the DGS in case of large pay-outs. Third, the question if the regional impact from disruption of critical functions should also be taken into account, in addition to the impact at national level. Fourth, a wider scope of the PIA, including a more comprehensive assessment of small and mid-sized banks. See also for further details, Veron (2019), Lastra et al. (2019) and Restoy et al. (2020). See also the Danish implementation of BRRD and operationalization of the PIA that in general leads to the application of resolution also in case of small and medium-sized banks (Finanstilsynet 2017).

[3] However, joint defaults of several institutions render a systemic crisis highly likely, which means that other factors endangering financial stability but not captured by this analysis become more important, such as confidence effects, fire sales and deleveraging on a broad scale. See Articles 5(6) and 10(3) BRRD for the consideration of system wide events in recovery and resolution planning.

are considered both when assessing the criticality of specific bank functions and when assessing the financial stability implications in case the bank would fail.[4]

Overall, the results show that a harmonized approach to estimate the potential impact on the real economy due to a credit shortfall caused by a bank failure is feasible, and that the proposed framework is applicable to banks of heterogeneous size and relevance. The application of the harmonized framework is especially useful for medium-sized banks, which can be considered "grey area" or "middle class" institutions, as defined by Restoy et al. (2020), as it provides insights to reduce the uncertainty on whether their resolution is in the public interest. At the same time, simulations suggest that the failure of similar banks could have effects of heterogeneous severity across jurisdictions.

While such a framework aims at enhancing the financial stability assessment in the PIA, it is acknowledged that it should be complemented by further elements. First, the framework only deals with the credit channel linking a bank failure to the real economy, disregarding other, equally important, channels. Second, the impact on the real economy is only one aspect of the financial stability consequences of a bank failure. Moreover, preserving financial stability is only one of the objectives to be assessed within a PIA, when deciding whether to deploy a resolution action instead of a NIP. Finally, quantitative considerations should be complemented with qualitative and expert judgement.

The rest of the paper is organised as follows. Section 2 summarises the scope of the common framework to assess the impact of a bank failure on the real economy via the credit channel and describes the steps through which the framework is implemented. Section 3 illustrates the outcome of the framework for four sample countries, notably Austria, Germany, Italy and Spain. Section 4 concludes.

2. An analytical framework: assessing the impact of a bank failure on the real economy through the lending function

2.1. From bank failure to real economy: the credit channel

Implications on the real economy are to be considered both when assessing the criticality of specific functions performed by the bank and when assessing the financial stability implications in case the bank would fail. The potential impact on real economy should be assessed in conjunction with a number of possible links between the management of a bank crisis and financial stability. For instance, direct or indirect contagion across financial institutions, also through confidence disruptions within the non-financial private sector (notably households and firms), might jeopardize the overall financial stability, which in turn can affect the real economy.

Figure 2.1 below shows the main transmission channels through which an abrupt bank failure could affect the real economy.[5] These correspond to the main functions performed by a bank: (i)

[4] See Art.2(1)(35) of BRRD, which defines critical functions as "*activities, services or operations the discontinuance of which is likely in one or more Member States, to lead to the disruption of services that are essential to the real economy or to disrupt financial stability […]*". See also Art. 6(3) of the Commission Delegated Regulation (2016/778) dealing with the substitutability of a function. Along these lines, the SRB "Introduction to resolution planning" document clarifies that in relation to the financial stability there is a need to account for real economy implications due to indirect contagion. Please see also the SRB document "Critical Functions: SRB Approach", available at https://srb.europa.eu/sites/srbsite/files/critical_functions_final.pdf.

[5] The transmission channels through which a bank failure can affect the real economy relates to the broader topic of links between the financial and the real economy sectors. For a short summary of the different transmission channels at work between the real economy and a bank failure, compare BCBS (2011), Ashcraft (2005) or Hoggarth et al. (2002).

functions reflected on the asset side of bank's balance sheet, (ii) functions reflected on the liability side and (iii) other intermediation services such as payment services.

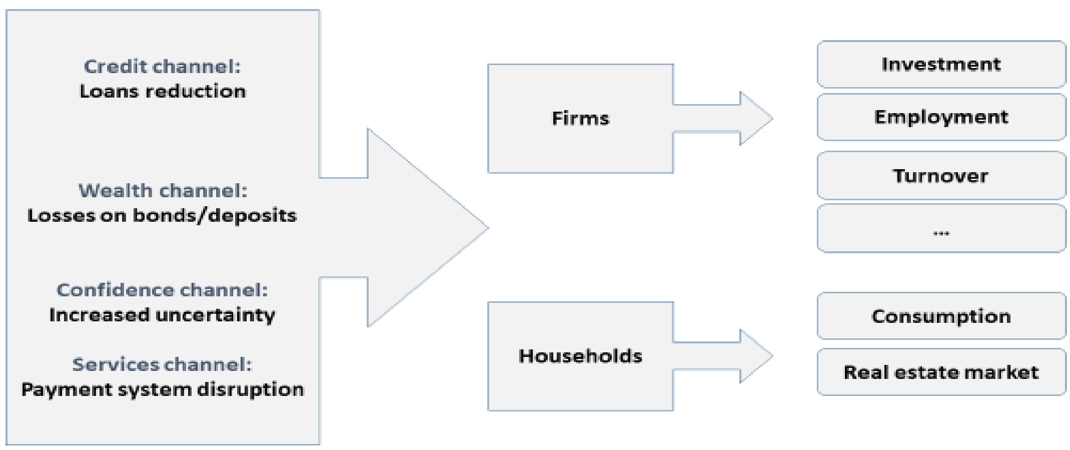
As for the asset side of banks' balance sheets, the credit channel plays a prominent role. A defaulting bank will no longer be able to lend to economic agents. This creates liquidity or credit constraints on borrowers, thus impairing their ability to produce, invest or employ. Additional negative effects possibly stem from the failure of banks that are heavily engaged in interbank lending.

On the liability side, the direct wealth effect created by the defaulting bank on its creditors, notably on its bondholders and depositors, is accompanied by a potential harm to the confidence in the entire financial system. For instance, households or firms hit by a financial loss on their investments in the ailing bank could reduce their consumption or investment plans, due to stricter budget constraints. Moreover, a bank failure can also trigger a general loss of confidence of investors in the financial system, which could be exacerbated by potential contagion of other banks if they experience direct losses.

Finally, a defaulting bank would prove unable to provide other banking services not directly reflected in its balance sheet. For instance, the bank's payment system function could be seriously impaired, thus slowing down the speed at which transactions related to real economy activities can be finalised.

The potential impact on the real economy of a bank failure should be assessed thoroughly, in order to further substantiate the critical function and financial stability assessment as part of the PIA. Against this background, the focus of our analysis is on the credit channel due to its crucial role for economic activities and welfare and due to the availability of readily applicable economic models.[6]

Figure 2.1. From bank failure to real economy: main transmission channels



Source: Authors' own elaboration.

[6] Nonetheless, this prioritisation is not intended to assign the credit channel an overarching role in the PIA with respect to other, equally important channels.

From an empirical point of view, bank lending is crucial in the euro area. Bank loans constitute almost 50 per cent of the external financing of euro area non-financial corporations (NFCs) in comparison with less than 25 per cent in the US (Altavilla et al., 2019). The high level of SMEs' bank dependency makes bank lending even more essential in the euro area. Bank lending also plays a leading role in the transmission of monetary policy to the real economy (Altavilla et al., 2019). Due to the leading role of banks in the financial system, multiple bank failures, depending on their management might weaken the ability of central banks to pass through their monetary policy stance to the economy.

Substitution of the bank lending function is generally challenging due to the huge content of information processing that characterizes the credit market, as acknowledged by the theoretical and empirical literature. According to the theoretical arguments, banks reduce information asymmetries between investors and borrowers insofar as, in originating loans and monitoring borrowers, they acquire private information, i.e. non-transferable or soft information, about customers and enhance the value of investment projects (Boot and Thakor, 2000). The empirical literature confirms that bank lending improves project payoffs relative to capital markets (Ongena and Smith, 2000).[7]

The importance of small and medium-sized banks could be underestimated if their lending function is not studied in detail. In comparison to large institutions, small and medium banks can also have a significant economic impact owing to their role in specific credit markets (e.g. local or specialized lending). In economies that are highly fragmented across sectors and regions, small and medium banks could have a significant impact on specific regions or sectors, whereas the macroeconomic impact at the national level may be small.

Finally, an additional reason to focus on the exploitation of the credit channel is the availability of harmonised data and established models to gauge the impact on the real economy (see next sections).

Within the credit channel, our analysis focuses on credit to firms (in particular NFCs) and, to a lesser extent, to households. The existing literature has emphasised the importance of the firm-credit channel.

Firstly, firms are the main sources of investment, employment, value added and foreign trade within an economy. We implicitly assume that – owing to the abrupt shutdown of credit relationships – entrepreneurs have to give up projects with positive net present value (Calomiris and Mason, 1994). In this respect, a thorough analysis of whether the failure of a bank mainly interrupts the flow of credit to low-quality ("zombie") firms rather than to creditworthy firms would be particularly useful. Similarly, households that suffer a credit shortfall are unable to consume or invest (e.g. for house purchase), thus further aggravating the situation of the firms.

Secondly, firms, and especially small firms, are borrowers whose risk assessment tends to be difficult and where banks can provide their highest added value. Reducing the information asymmetries by building solid credit relationships through repeated and close interaction with a lender is more important for such firms than for other borrowers. Therefore, in the short term, a failed lender is harder to replace. This hold notably for small and medium-sized firms, which, compared to other borrowers, such as large firms, often only have one main banking relationship (Baas and Schrooten, 2006).

[7] Nevertheless, it should be recognized that current advances in technology, the appearance of new players in the lending market and the efforts to disintermediate credit markets make it difficult to estimate whether bank lending will be more or less substitutable in the future. It is noteworthy that bank credit to NFCs represented 70 per cent of global external financing in the period 2002-2008 and later decreased to 50 per cent, following the Global Financial Crisis.

Thirdly, and in contrast with credit to firms, credit to households for consumption and investment, can be more easily substituted through other banks. The main form of credit to households, i.e. real estate mortgages, are standardised loans with long-term repayments usually allowing households to negotiate loan extension in advance if needed or to search for alternative sources of new mortgages, hence easing the substitution of a defaulting bank.

In spite of the prominence of the credit channel, the analysis of the impact on the real economy of a bank's default could be developed further to incorporate the other transmission channels. Therefore, an initial focus on the (firm) credit channel has to be seen as a first concrete step to provide a comprehensive assessment of the potential real economy spillover of a bank failure, which needs to be complemented with the analysis of the already-mentioned channels.

2.2 A two-step approach to estimate real economic impacts of a bank failure

The adopted empirical framework employs a two-step approach to quantify the impact of a bank failure on the real economy through the credit channel. In Step 1, the size of the credit shortfall induced by the failure of a specific lender is calculated, whereas Step 2 is aimed at retrieving bank- specific or country-average multipliers to translate this credit shortfall into an impact on the real economy.

To estimate the credit shortfall (Step 1), we need to identify which parts of an ailing bank's loan book are likely to be lost following an abrupt closure of the ailing bank. By contrast, the orderly resolution of the lender is assumed to have a negligible repercussion on its lending activities. We assume that if a bank is shut down, existing loans will not be rolled-over and credit lines will be cancelled. We consider that, in the short-run, it is unlikely that firms and households will be able to replace any credit due or the credit lines, hence the credit shortfall under Step 1 would amount to the sum of credit with short-term residual maturity and revocable credit. To overcome data limitations, we produce different estimations of the credit shortfall using alternative definitions of credit with short-term residual maturity and of revocable credit. It must be remarked that any estimated credit shortfall refers to the short term, which we define to be 12 months, since it can be assumed that any lender can be replaced in the longer run.[8]

In Step 2, we gauge how a credit shortfall impacts the real economy, estimating the effect ("multiplier") on macroeconomic variables such as GDP, value added, or employment. This effect is calculated using bank-specific or country-average credit shortfall multipliers. For such an estimation, different models can be used that can be grouped along the following dimensions: (i) past bank failures vs model-based credit supply shocks, (ii) "General vs Partial equilibrium" econometric approach, as well as (iii) macroeconomic vs microeconomic data. In the following, these dimensions are briefly reviewed.

(i) Past bank failures allow to precisely identify the exogenous credit supply shock and to estimate a real effect multiplier, but it is not straightforward to generalise the specific outcomes to different

[8] In contrast to these direct effects, indirect credit shortfall stemming from other banks that might be impacted by the specific bank failure is out of the scope of this analysis. While this "indirect" credit shortfall can be economically significant, its estimation would require detailed knowledge of the network of links among financial institutions, including the amount, seniority and nature of assets cross-holdings. For an example of the complexity of the analysis involved in such a contagion mechanism, see Covi et al. (2019).

institutional settings and periods.[9] For this reason, other empirical studies leverage large sets of panel data to disentangle supply-side credit shocks and put those into relation with real outcomes. Such models are more general in their conclusions and do not require a systematic track record of historical bank failures, but they are less precise than those estimating the real outcome from historical episodes.

(ii) Regarding the second dimension, a general equilibrium model tries to explain the dynamics of demand and supply involving several agents and markets, based on the notion of an economy-wide equilibrium. Most literature assessing the impact of financial sector dynamics on the real economy utilizes vector autoregression (VAR) models. Such econometric models allow to generate impulse-response functions to temporary shocks of the variables included in the model and hence to estimate the real economy multiplier.[10] Alternatively, partial equilibrium econometric models focus on the relation among the variables of interest within a specific market, but cannot capture economy-wide and feedback effects and usually require large sets of panel data.[11]

(iii) As for the third dimension, it is important to decide which data are to be used and its availability. For instance, VAR models have traditionally been based on macroeconomic variables,[12] which are often publicly available. On the other hand, the usage of microeconomic data is becoming increasingly common, due to the growing availability of granular data at the individual agent level over longer time horizons that allow constructing panels.[13] Usually, micro-level data is used within partial equilibrium approaches, but these borders are becoming progressively blurred.[14]

[9] Examples include Beck et al. (2018), who show that banks that were more exposed to the bail-in of a resolved Portuguese bank significantly reduced credit supply, and Fukuda and Koibuchi (2006) who focus on the failure of two large Japanese banks to show that a sudden loan restriction affected small firms significantly stronger than large firms.

[10] For instance, Kupiec and Ramirez (2013) use a VAR model to show that bank failures have long-lasting negative effects on economic growth. Ramirez and Shively (2012) use a structural moving-average model on US-data before the Great Depression and find that the real impacts can be attributed both to a reduction in consumption from the slow liquidation of failed-bank deposits, as well as to a decrease in investment from a disruption of credit to bank-dependent firms. Hristov et al. (2012), through a panel VAR, find heterogeneous supply shock effects across the Euro area during the Great Financial Crisis.

[11] Greenstone et al. (2019) gauge the credit channel's impact on the real economy with regard to the market for small business loans leveraging the substantial heterogeneity across banks in their year-to-year variation in lending along with geographic variation. Puri et al. (2011) use granular data on loan applications and approvals for German savings banks to distinguish between demand and supply effects during the financial crisis, finding that the banks more affected by the US financial crisis reject substantially more loan applications than unaffected banks. Guler et al. (2019) offer a comprehensive overview on the literature that assesses the real effects of bank credit supply by using data on lender-borrower relationships, either on granular firm level or on a more aggregated level. Amiti and Weinstein (2018) use Japanese bank-firm level data to separate firm borrowing shocks from bank supply shocks and show that supply-side financial shocks have a large impact on firms' investment. Using a matched dataset on jobs, firms' balance sheets and bank-firm relationships for one Italian region, Berton et al. (2018) show that contraction in credit supply explains one fourth of the reduction in employment. Barone et al. (2018) retrieve a measure of local credit supply for Italian provinces which they show to affect real value added as well as, to a lesser extent, employment, following the financial crisis but that during the pre-crisis period however, credit supply shocks affected lending volumes but not real outcomes. Degryse et al. (2018) use a very granular matched bank-firm credit dataset from Belgium and show that firms borrowing from banks with a negative credit supply shock exhibit lower investments, while positive credit supply shocks are associated with bank risk-taking behaviour.

[12] For example, among the studies mentioned previously, those by Ramirez and Shively (2012) and by Kupiec and Ramirez (2013) rely purely on macroeconomic data.

[13] See among others Greenstone et al. (2019), Berton et al. (2018), Barone et al. (2018), Amiti and Weinstein (2018), Beck et al. (2018), and Puri et al. (2011).

[14] For example, Budnik et al. (2019) use macroeconomic data in combination with bank-individual micro data to build their FAVAR model.

After considering all the trade-offs explained above, and in particular data and model availability, the proposed framework estimates the "credit-to-real economy multiplier" (Step 2) by following two distinct but complementary models. We use first a Factor-Augmented Vector Auto-Regressive model (FAVAR) model inspired by Budnik et al. (2019) that allows to evaluate the response or multipliers of value added, GDP or other macro variables to a credit supply shock. Then we also follow a micro-econometric approach in the vein of Greenstone et al. (2019) and related literature; this second estimation strategy also offers a robustness check for the outcomes of the first model. This model allow to identify bank-specific supply shocks in given credit market segments, aggregate them and finally estimate the country-average real economy multiplier through a regression.

In principle, both approaches can be adjusted to duly reflect sensitivity to the economic and financial cycle. It is possible to combine FAVAR models with time-varying parameters to take into consideration the cyclicality of economic and financial conditions (see Eickmeier et al., 2011). Using the approach by Greenstone et al. (2019), sensitivity to cyclical conditions could be achieved by running separate estimations for different historical states of the economy, conditional on the availability of long enough time series.

Moreover, the framework allows taking into account a possible regional dimension of the PIA. In fact, the first step (credit shortfall) can also be estimated with regard to the outstanding credit within a subnational area, rather than at the level of the entire Member State. This quantifies a regional credit shortfall and – through the Step 2 multiplier – it can be translated into a real economy impact, which is relevant at regional, rather than national, level.

2.3 Step 1. Estimating the credit shortfall from a bank failure

Definition of credit shortfall and methodology: Baseline amount and additional effects

Within the proposed methodology, the aim of Step 1 is to gauge the credit shortfall that would hit firms and households upon an abrupt bank failure in which the bank is liquidated under NIPs. By contrast, within an orderly bank resolution it is assumed that business continuity is ensured, outstanding credit is maintained and loans, including those maturing shortly after the failure, can be rolled over.

In principle, it can be argued that upon an abrupt bank failure, as often occurs in national frameworks of NIPs, assets are piecemeal liquidated and portfolios not transferred to another bank. This implies also that (1) loans would not be renewed upon expiration and (2) the failed bank would revoke some or all of the extended credit lines. Moreover, in some jurisdictions the possibility of revoking credit lines is limited to undrawn amounts.

To capture both dimensions of the credit shortfall resulting from NIPs, the concept of credit with short-term residual maturity is used along with the concept of revocable credit.[15] Under the baseline approach, the credit shortfall is estimated taking into account the outstanding credit with

[15] A concern on how to estimate the credit shortfall is associated to the presence of heterogeneous credit revocation rules under the different national frameworks of NIPs. Accordingly, in April 2019 a stocktaking exercise was carried out at selected jurisdictions, contributing to this paper (Austria, Finland, Germany, Italy and Spain). In the majority of the surveyed cases, the possibility to revoke a loan hinges on the question of whether the credit has been disbursed or not at the time of the opening of the liquidation proceedings, concluding that only the undrawn part of a credit can be revoked.

short-term residual maturity (up to 12 months). Two additional effects take into account the notion of revocable credit: the amount of undrawn credit lines at the failed bank could be included to amplify the credit shortfall, whereas the usage of undrawn credit lines at other (non-failed) banks with which lending relationships already exist, could allow the borrowers to mitigate their credit shortfall. Finally, a lower bound scenario is also defined, as the one in which the credit shortfall under the baseline approach is estimated only for single-lender borrowers, i.e. those borrowers of the failed bank without other banking relationships. Table 2.1 below summarizes the framework to perform Step 1 estimation. The credit shortfall is calculated at bank level, with reference to a given jurisdiction and for two classes of counterparties, non-financial corporations (NFCs) and households. The shortfall is defined both in absolute terms (amount of credit at risk) and in relative terms (credit at risk as a percentage of total credit in the relevant market).[16] To gauge the impact of a bank failure at regional, rather than at national level, the percentage credit shortfall could be calculated against a regional aggregate denominator (e.g. including one or more regions, which are relevant for the failed bank).

Table 2.1. A framework to estimate Step 1

(A) Baseline amount
Short-term credit: loans that are about to mature and will not be renewed upon expiration can be measured based on two alternative solutions:
Benchmark solution: loans with residual maturity ≤ 12 months, when information on residual maturity is available
or, if the benchmark solution is not applicable due to data limitation,
Fall-back solution: short-term credit products, when information on type of products which are typically short-term is available
(B) Additional effects (1)
Revocable loans: the disposable amount of credit lines and the revocable amount of fixed-term loans, when applicable, can be taken into account based on two add-ons:
When balance sheet information on drawn and undrawn amounts of credit lines is available and / or information on revocable credit.
Additional 1: Amplifiers (+) baseline amount plus undrawn amounts of credit lines contractually granted by the liquidated bank, which were not yet used by the borrowers at the time of failure. The ultimate effect is to increase the credit shortfall estimated under the baseline.
Additional 2: Mitigants (-) baseline amount minus undrawn amounts of credit lines available through other banking relationships that borrowers can still withdraw to mitigate the credit shortfall produced by the liquidated bank. The ultimate effect is to reduce the credit shortfall estimated under the baseline.
(C) Lower bound hypothesis (2)
A lower bound limit to the credit shortfall could be established considering only short-term credit granted to borrowers of the failed bank that have no other lenders at all.

Source: Authors' own elaboration.

[16] To this end, a denominator has to be calculated to scale the estimated loss of credit. The denominator is set equal to the total bank credit extended in the relevant jurisdiction to the relevant sectors (i.e. NFCs, households or both), according to the data source underpinning the estimation of the credit shortfall. Banks, which are part of the reporting population, shall be included in the analysis, even when they do not grant any short-term or revocable credit.

Data description: EU harmonized credit data sources

In order to estimate the credit shortfall, three EU harmonized credit data sources can be utilised: ECB's databases Balance Sheet Items (BSI), Analytical Credit dataset (AnaCredit), and the Financial Reporting (Finrep) introduced with the EU Capital Requirements Directive (CRD).

Since none of these data sources is able to provide a comprehensive coverage of the dimensions that are relevant to perform the Step 1 estimation under the common framework (e.g. full reporting population, maturity brackets, etc.), a range of possible quantifications using different data sources of the credit shortfall is provided. Table 2.2 provides an overview of the different data source options to implement the common framework to perform the Step 1 estimation. BSI is the preferred solution, since it reports the residual maturity of loans and thus complies with the requirements for a precise estimation in most jurisdictions, in spite of a lower granularity than that provided by AnaCredit. BSI also allows for the Step 1 estimation through product type data, implementing the fall-back solution based on credit products that are likely to have only short-term original maturities. As far as NFCs are concerned, another option to implement the framework to perform Step 1 is AnaCredit[17]; AnaCredit contains granular (loan level) data on credit exposure, including their maturity date, and thus complies with the requirements for a precise estimation in all jurisdictions.[18] While BSI and AnaCredit allow to implement the concept of "credit with short residual maturity", Finrep only enables to estimate a less precise credit shortfall based on product type data (contained in Finrep template 05.01), which proxy the concept of revocable credit.

Table 2.2. Credit shortfall. Estimation solutions.[1]

	NFCs credit shortfall		Households credit shortfall	
	Short-term solution	**Long-term solution**	**Short-term solution**	**Long-term solution**
Baseline 1	BSI (benchmark)	BSI (benchmark)	BSI (benchmark)	BSI (benchmark)
Baseline 2	BSI (fall-back)	AnaCredit (benchmark)	BSI (fall-back)	BSI (fall-back)
Baseline 3	Finrep (fall-back)	BSI (fall-back)	Finrep (fall-back)	Finrep (fall-back)
Baseline 4		Finrep (fall-back)		
Additional 1		AnaCredit (benchmark) + amplifiers		
Additional 2		AnaCredit (benchmark) + amplifiers – mitigants		
Additional 3		AnaCredit (benchmark) (lower bound)		

Source: Authors' own elaboration.

Notes: (1) Short-term solution = as long as AnaCredit data is not available. Long-term solution = upon availability of AnaCredit data. Baseline = estimations based on extended and used credit. Additional = estimations based on undrawn credit lines or single-lender relationships. Benchmark solution = estimations based on the residual maturity of credit (≤12 months). Fall-back solution = estimations based on the technical form of loans, i.e. product type.

[17] AnaCredit does not contain data on households.

[18] The higher granularity contained in AnaCredit brings along the complexity of this database, which was only implemented in all jurisdictions in 2018, and which is not fully available yet for data exploitation at NRA level.

2.4 Step 2 - From credit to real economy: Macro-econometric model

This section describes a methodology to assess the impact of the estimated credit shortfall from the failing bank on real economy variables. To this end, we estimate "multipliers" that show to what extent a given amount of credit shortfall translates into real economy effects, for a specific bank or in a specific country. As a first solution, we employ a factor-augmented vector-autoregressive (FAVAR) model that allows to link a rich set of bank-level data, coming from a dataset that can be built using EU-harmonised data (Finrep and Corep templates), to macroeconomic aggregates. This approach puts together micro (bank-level) and macro data, combining the standard VAR analysis with factor analysis.

First, we estimate a FAVAR model at country level; then, from the model, we derive responses of real economy variables (e.g. GDP, or value added) to a credit supply shock to firms. To this end, we follow the approach by Budnik et al. (2019), which explores the merits of a structural factor-augmented vector autoregression model for the assessment of macroprudential policies.

Model description

Our model, as in Bernanke et al. (2005), is a structural VAR model in the [(M+K) * 1] vector of endogenous variables $F_t = \left[F_t^y F_t^x\right]$, where F_t^y is the [M * 1] vector of observed variables and F_t^x is the [K * 1] vector of unobserved common factors:

$$AF_t = \Gamma(L)F_{t-1} + e_t \qquad \text{[eq. 2.4.1]}$$

A is a matrix of parameters and $\Gamma(L)$ is a matrix lag polynomial, both A and $\Gamma(L)$ of dimension [(M+K) * (M+K)] and $e_t \sim i.i.d.(0, \Omega)$ is a [(M+K) * 1] vector of structural shocks with mean zero and diagonal covariance matrix Ω. The reduced-form representation of the model is:

$$F_t = \phi(L)F_{t-1} + \epsilon_t \qquad \text{[eq. 2.4.2]}$$

where $\phi(L) = A^{-1}\Gamma(L)$ and $\epsilon_t = A^{-1}e_t \sim N(0, \Sigma)$ with $\Sigma = A^{-1}\Omega A$. The [(M+K) * 1] vector ϵ_t includes the reduced form innovations.

The latent factors F_t^x are computed on the basis of a large set of N time series contained in $\boldsymbol{X}_t$, the latter consisting of a number of banking sector variables observed across different banks. The observation equation that links the [N * 1] vector X_t of observable variables to observed and unobserved factors in F_t is:

$$X_t = \Delta^y F_t^y + \Delta^x F_t^x + u_t = \Lambda F_t + u_t \qquad \text{[eq. 2.4.3]}$$

where Δ^y and Δ^x are, respectively, [N * M] and [N * K] matrices of factor loadings, which measure the sensitivity of the individual variables in X_t to each common factor (observed and unobserved), and u_t is a [N * 1] vector of idiosyncratic disturbances assumed to be normally distributed with mean zero and diagonal covariance matrix H. Usual assumptions apply: (i) orthogonality between latent factors and observed variables and mutual orthogonality between latent factors; (ii) no correlation between disturbances and factors, $E\left[u_{it}\, u_{js}\right] = 0, \forall i, j = 1..N$ and $\forall t, s = 1,..T, t \neq s$.

The country model is estimated in two stages, as in Budnik and Bochmann (2017). In the first stage, we select the observed variables and estimate the unobserved factors based on a large set of bank-level data using principal component analysis. When choosing the number of unobserved factors, i.e. the principal components, to be used in the VAR model, the aim is to explain at least 50 per cent of the contemporaneous variation in bank-level variables (on average).[19] With this procedure, a large share of the co-movement between banking variables is exploited. In the second stage, we estimate the reduced form VAR model.

The structural shocks are identified by zero and sign restrictions on the observed macro-financial variables, applying the approach proposed by Arias et al. (2018) to obtain draws of the corresponding impulse-response functions (IRFs) of the endogenous variables to structural innovations. Identifying restrictions are taken from mainstream literature (e.g. Barnett and Thomas, 2013). We impose the restrictions on the quarter when the shock occurs. The aggregate demand and supply shocks are included to ensure that credit supply shocks are exogenous rather than endogenous responses to macroeconomic conditions. A negative credit supply shock is identified on the basis that it would typically lead to an opposite movement between credit spreads and lending (i.e. rising spreads with a simultaneous reduction in the volume of lending). The zero and sign restrictions used to identify structural shocks are summarised in Table 2.3.

Table 2.3. Identification of structural shocks

	GDP	GDP Deflator	Lending margins (1)	Deposit margins (2)	NFC loans
Aggregate demand shock	+	+			
Aggregate supply shock	+	-			
Negative credit supply shock	0	0	+	+	-
Negative loan demand shock	0	0	-		-

Source: Authors' own elaboration.

Notes: (1) Lending margin is the difference between interest on loans to NFC and interest on deposits by NFC. (2) Deposit margin is a measure of funding costs, defined by deposit rate on new deposits to non-financial corporation – EONIA (proxy for risk-free rate).

Data description

In the vein of Budnik et al.'s (2019) model, the vector of observable variables includes real value added or GDP growth rate and their deflators, lending margins, the spread between the EONIA and retail deposit rate (as a proxy for funding costs), and the bank-level total outstanding loans to NFCs. Therefore, the focus is on the lending to the non-financial private sector. At bank-level, we consider the credit institutions under the SRB's remit of the four countries included in the sample (Austria, Germany, Spain and Italy). More specifically, the sample covers the Significant

[19] The threshold of at least 50 per cent of variance of the contemporaneous variation in bank-level variables is in line with the main empirical literature (see Budnik et al., 2019).

Institutions (SIs): 8 for Italy, 11 for Spain, 13 for Germany, 6 for Austria. Generally, the data sample covers the period 2014Q3-2019Q1.[20]

Bank-level information at a consolidated level is used in the current version of the model. The main reason to employ data at consolidated level is the relatively short length of the solo level time series.[21] A few adjustments for the larger international banking groups, notably in Spain, might be considered in the further refinement of the model to take in due account the large amount of foreign exposures.

When selecting bank-level variables, the focus is on measures of credit to NFCs and households, non-performing loans, impairments on loans and provisions, bank profitability and capitalisation (ROE and ROA, Tier 1 capital) and bank liquidity (loan-to-deposit-ratio). The bank-level data included in the model are summarised in Table 2.4.

The selection of the bank-level variables is a fundamental step as it allows to capture the latent factors (or principal components) to be included in the FAVAR model. Operationally, the latent factors are obtained by using the principal component analysis (PCA) for all countries included in the sample. Principal components allow to reduce the dataset dimension for a feasible estimation, and lend themselves to economic interpretation. For the four countries in the sample, the first principal component reflects the dynamics of bank-level total assets and credit variables, while the second principal component summarises the dynamics of the bank capitalisation and the third principal component describes the dynamic of profitability indicators.

Table 2.4. Bank-level data

1.	Total assets
2.	Total lending
3.	Total outstanding loans non-financial corporations (NFCs)
4.	Total outstanding loans households (HHs)
5.	Total NPLs / Total loans
6.	Tier 1 Capital
7.	Tier 1 / Total RWAs
8.	Loan to deposit Ratio
9.	Profit net of extraordinary profit and taxes / Total assets
10.	ROA

Source: Authors' own elaboration.

2.5 Step 2 - From credit to real economy: Micro-econometric model

As an alternative to the FAVAR model illustrated in the previous section, this section outlines a micro-econometric model to quantify the credit-to-real economy multipliers at country level. Differently from the FAVAR approach, in this case there is no attempt to model the dynamics of the economic and financial system as a whole, but a reduced form estimation from the credit supply shock to the final outcome variable (e.g. gross value added, or total employment) is performed.

[20] For Germany and Austria, the data sample also covers 2019Q2.

[21] For instance, in the case of Spain, the banks have been reporting Finrep at solo level since June 2016 and Corep at solo level since December 2014.

Model description

The identification strategy of the micro approach is based on previous works done by Greenstone et al. (2019), Degryse et al. (2018) and Barone et al. (2018).

The basic intuition underpinning the micro approach starts from the acknowledgement that the evolution of loan growth is driven by both demand-side and supply-side factors. From a micro-economic perspective, the demand for loans arises from the varying funding needs of borrowers. Indeed, firms, which are at the centre of the current analysis, mainly require external financing to fund fixed investment, inventories and working capital, as well as research and development. In contrast, the supply of loans is depending on a bank's characteristics: its willingness to lend, which is mainly depending on the creditworthiness of the potential borrower, and its capability to lend, which is contingent on its own solvency, among other factors. As banks are usually lending within more than one credit market segment, the empirical approach allows us to control for the credit demand from each specific segment, and thus to identify the effect of a bank's individual characteristics on the provision of its loans, i.e. the supply-side factors which drive loan provision.

The following equation can be estimated for each segment *s* = 1, …N, defined as the borrowing firms' industry, location or size, or a combination of those:

$$\Delta L_{bst} = \alpha + \delta_{bt} + \gamma_{st} + \varepsilon_{bst} \qquad \text{[eq. 2.5.1]}$$

where the outcome variable is the percentage change in the outstanding amount of loans (L_{bst}) granted by bank *b* to segment *s* between the time *t-1* and *t*; δ_{bt} is a dummy variable that measures the individual effect on the overall loan growth rate of bank (*b*) in period (*t*). γ_{st} is a dummy variable to control for factors in segment (*s*) in period (*t*) that affect the loan growth rate and is able to proxy for segment-time variant demand for loans. Hence δ_{bt} is the coefficient of interest of equation [2.5.1], that can be interpreted as the credit supply shock.

Next, a credit supply index (S_{st}) for each segment in each period is constructed by aggregating the bank-specific supply shocks estimated in equation [2.5.1], weighted by the lagged market share of each bank in the respective segment, as follows:

$$S_{st} = \sum_{b} w_{bs(t-1)} * \widehat{\delta_{bt}} \qquad \text{[eq. 2.5.2]}$$

where $\widehat{\delta_{bt}}$ are the time-varying bank fixed effects estimated in equation [2.5.1] and $w_{bs(t-1)}$ is bank b's market share in the segment *s* in the previous period.

In the final step, the credit supply index S_{st} is used to explain the supply side-driven variation of real macroeconomic variables such as value added and employment. More specifically, we run a panel data regression of the following form:

$$y_{st} = \alpha + \eta_s + \gamma_t + \beta S_{st} + \varepsilon_{st} \qquad \text{[eq. 2.5.3a]}$$

where y_{st} is the growth rate of the real economy variables in segment s at time t; η_s and γ_t are segment- and time-fixed effects, respectively; S_{st} is the segment-time specific credit supply indicator taken from equation [2.5.2]. β represents the elasticity of the real outcome variable to the variation in credit supply and can be regarded as the real economy multiplier. The expected sign of β is positive, i.e. a positive credit supply shock has a positive impact on the real economy variable. The credit supply indicator is incorporated on the right-hand side of the equation at different lags as it can be assumed that firms' decisions with respect to investment and employment following a credit supply shock will only materialise after a certain period of time.

To increase the panel size and the precision of the estimation, equation [2.5.3a] can be extended to cover more countries *c*, thus taking the following form:

$$y_{stc} = \alpha + \eta_{sc} + \gamma_{tc} + \beta_c S_{stc} + \varepsilon_{stc} \qquad \text{[eq. 2.5.3b]}$$

The credit supply index S_{stc} is retrieved, as in equation [2.5.3a], from the country-specific estimations using equation [2.5.1] and [2.5.2], whereas η_{sc} denotes a country-segment fixed effect and γ_{tc} is a country-time fixed effect. β_c is the country-specific multiplier of interest.

Data description

The choice of data used to perform the micro-econometric estimate strikes a balance between the granularity of information on the lender-borrower relationships and the availability of harmonised data sets on the European level. Adequate data sources on credit provision by segment are Finrep as well as AnaCredit. The Finrep template 06.01 provides a segment-breakdown by the borrowing firm's industrial sector according to the NACE classification.[22] AnaCredit allows to break down the credit outstanding by regional segments (at NUTS2 or NUTS3 level[23]), by industries (at two digit NACE classification level), by firm size class or by a combination of these criteria. As for the finer segment definition, however, it should be kept in mind that real economy outcome variables (e.g. value added or employment) are not always available on such a granular level in an EU-harmonised format, i.e. through Eurostat.

Harmonised time series of real economy data to be used as dependent variables in equation [2.5.3] are provided by Eurostat. We employ real economy data at the same breakdown level as data on credit provision. Eurostat provides real economy data by geographical area, by NACE industries as well as a breakdown by both geographical area and industry, i.e. NUTS2/3-by-NACE, for a few statistics. In terms of sample coverage, the micro-econometric estimation of Step 2 is applied to the credit institutions under the SRB's remit of three countries, i.e. Germany, Spain and Italy.

Even though AnaCredit is the most granular harmonised dataset on credit provision, at the current juncture it still lacks a sufficiently long time series to perform the required estimations. Finrep is available from at least 2017. Eurostat provides real economy outcomes at NACE level for the same periods. The present framework, therefore, employs Finrep quarterly data with segments defined at NACE-level (Finrep template 06.01), coupled with Eurostat data on real gross value added and total employment, with the same industry-level detail. Finer estimation through AnaCredit will likely become feasible in the future, as soon as sufficiently long time series will become available, i.e. a length of at least 3 to 5 years. A longer-term solution could therefore include sectoral estimations based on both Finrep and AnaCredit, while AnaCredit data could be also used to define segments at region and region-by-sector level.

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[22] NACE is the European Statistical Classification of Economic Activities.

[23] NUTS is the European Nomenclature of Territorial Units for Statistics.

3. Illustrative results

This section describes the illustrative results obtained from the simulations performed for the countries of the sample. The outcome of the simulations is reported principally to illustrate how the different parts/steps of the model work together and to provide a guidance for potential users of the model, rather than to show conclusive estimations of the parameters of interest.

Step 1 and Step 2 results

Step 1 (credit shortfall) is simulated recurring to different data sources (BSI and Finrep) and to different definitions within each data source, as highlighted in Section 2.3. Table 3.1 presents the descriptive statistics for the estimated credit shortfall by category of banks per country. The fall-back estimations, based both on BSI and on Finrep, are lower than the benchmark ones, solely based on BSI. This is an expected outcome: fall-back estimations rely on the type of product to proxy lending that likely has only short-term original maturities, and disregard other (fixed term) loans with a short residual maturity. This latter portion of credit is by contrast included in the benchmark BSI-based estimation.

Table 3.1. Step 1. Credit shortfall estimations[1]

(percentage values; credit shortfall as a percentage of total credit to the segment of borrowers; data as at 31.12.2018)

	BSI – benchmark			**BSI - fall-back**			**Finrep**		
	NFCs	House-holds	Total	NFCs	House-holds	Total	NFCs	House-holds	Total
1. Austria									
O-SII	1.47	0.29	0.84	0.91	0.27	0.56	[n.a.]	[n.a.]	[n.a.]
Other SI	0.07	0.04	0.05	0.06	0.04	0.05	[n.a.]	[n.a.]	[n.a.]
LSI	0.02	0.01	0.02	0.02	0.01	0.02	[n.a.]	[n.a.]	[n.a.]
Other banks	0.05	0.02	0.03	0.01	0.00	0.01	[n.a.]	[n.a.]	[n.a.]
Country average	*0.05*	*0.02*	*0.03*	*0.04*	*0.02*	*0.03*	*[n.a.]*	*[n.a.]*	*[n.a.]*
2. Germany[2]									
O-SII	0.57	0.09	0.26	0.24	0.03	0.10	[n.a.]	[n.a.]	[n.a.]
Other SI	0.06	0.03	0.03	0.02	0.02	0.02	[n.a.]	[n.a.]	[n.a.]
LSI	0.01	0.00	0.00	0	0.00	0.00	[n.a.]	[n.a.]	[n.a.]
Other banks	0.02	0.01	0.01	0.01	0.01	0.01	[n.a.]	[n.a.]	[n.a.]
Country average	*0.01*	*0.04*	*0.01*	*0.01*	*0.00*	*0.00*	*[n.a.]*	*[n.a.]*	*[n.a.]*
3. Spain									
O-SII	3.99	0.59	1.95	2.20	0.33	1.08	1.92	0.35	1.02
Other SI	0.74	0.11	0.36	0.46	0.07	0.23	0.20	0.08	0.13
LSI	0.02	0.01	0.01	0.02	0.00	0.01	0.01	0.00	0.00
Other banks	0.04	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Country average	*0.18*	*0.03*	*0.09*	*0.10*	*0.02*	*0.05*	*0.08*	*0.02*	*0.04*
4. Italy									
O-SII	5.96	1.71	3.92	2.42	0.76	1.62	2.94	0.73	1.88
Other SI	1.39	0.53	0.98	0.78	0.20	0.50	0.71	0.19	0.46
LSI	0.04	0.02	0.03	0.02	0.01	0.02	0.03	0.01	0.02
Other banks	0.09	0.06	0.07	0.03	0.01	0.02	0.12	0.04	0.08
Country average	*0.22*	*0.08*	*0.15*	*0.10*	*0.03*	*0.07*	*0.14*	*0.04*	*0.09*

Source: Authors' own elaboration.

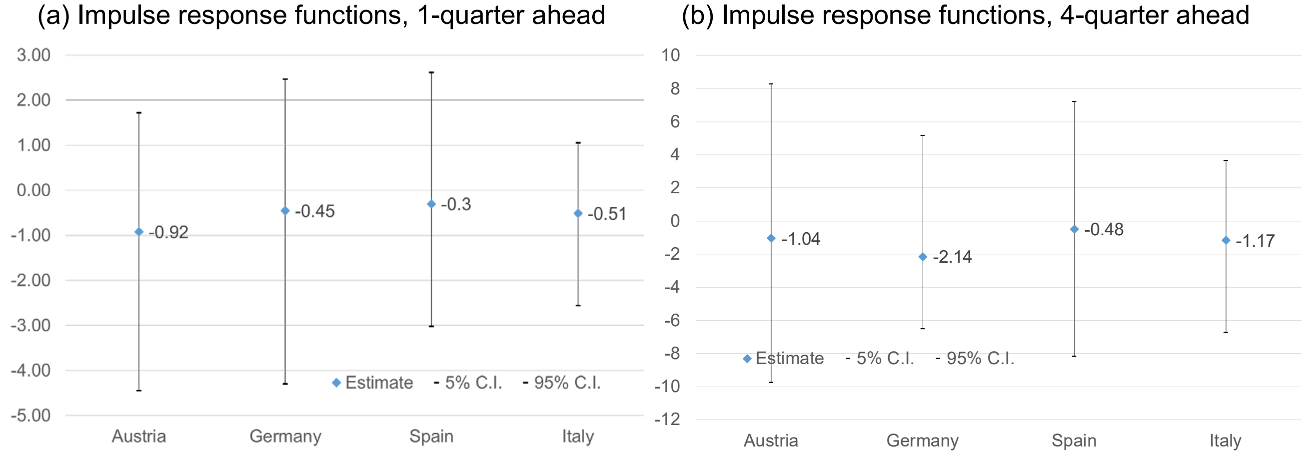
Notes: (1) Credit shortfall for the average bank within each class, as a percentage of total bank credit to the same sector (NFCs, households) in the country. The four bank classes are: 1) O-SII, other systemically important institutions; 2) SI, other Significant institutions different from O-SII; 3) LSI, less significant institutions; 4) other banks. – (2) Data for Germany are from national balance sheet statistics on which BSI data are based as the NRA could only access the former.

Table 3.1 shows, for instance, that in Germany the failure of a Significant Institution different from a systemically important bank ("other SI") produces a potential credit shortfall for NFCs equal to 0.06 per cent of the total credit to firms in the country. For an Austrian other systemically important institution (O-SII), this credit shortfall is equal to 1.47 per cent of the national outstanding credit to NFCs. Significant variability in average values emerges across countries, but also within countries and within each country's subsample. This depends on the concentration of the banking sector but also on the variety of bank business models across and within jurisdictions, which are correctly accounted for by applying the framework on the individual bank level.[24]

[24] For instance, within each subsample there are banks with a brick-and-mortar business model, mainly devoted to lending to firms and households, and other banks more focused on non-lending business (e.g. securities-related activities). The methodology to estimate credit shortfall on individual bank level correctly accounts for this heterogeneity.

Regarding the estimation of the credit-to-real economy multipliers, based on our FAVAR framework, Figure 3.1 displays the country-average response of the endogenous real economy variables to a one percentage point negative credit supply shock (based on NFC credit), one and four quarter-ahead. In this example, the estimation is performed in terms of GDP impact, but it could also be performed with reference to other real outcomes, e.g. to value added, to increase comparability with the estimates from the micro-econometric model. The results should be seen as first model-based estimations and not as final assessment of the impact stemming from the credit channel.

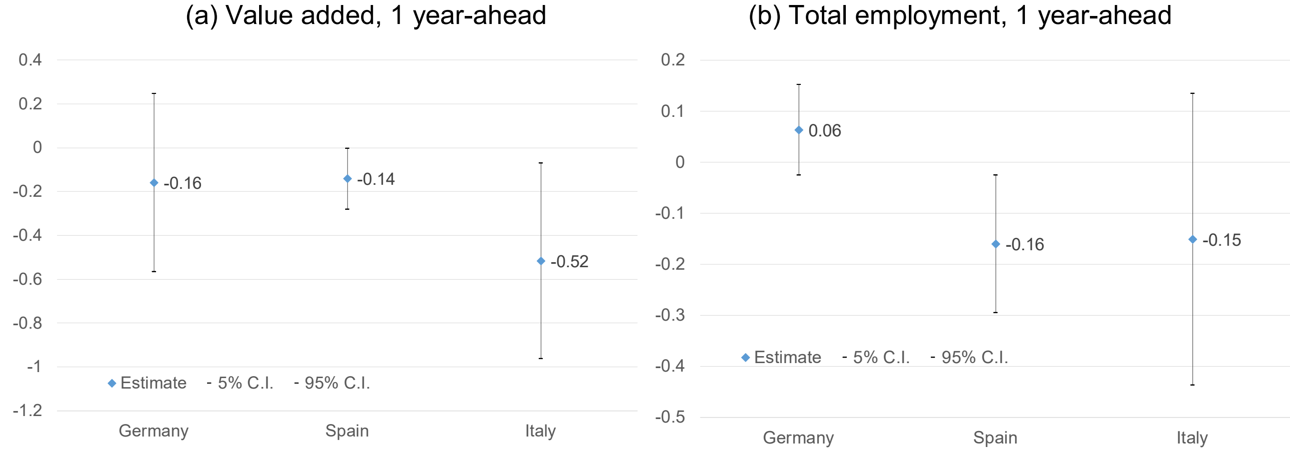
Figure 3.1. Step 2 FAVAR model estimations. Impact on gross domestic product (GDP)[1]



Source: Authors' own elaborations (FAVAR model).
Notes: (1) Impulse-response functions (IRFs) of macroeconomic variables (GDP) to a credit supply shock. Impact in percentage on the level of GDP of a credit shock = 1% of total NFC credit, ceteris paribus. The bars display 5 – 95 per cent confidence intervals.

The credit-to-real economy multipliers can also be estimated using the micro-econometric model, as described in section 2.5. Based on this alternative approach, the estimations of the impact of the credit shortfall (based on NFC credit) triggered by a bank failure on value added and employment one-year ahead are displayed in the Figure 3.2.

Figure 3.2. Step 2 micro-econometric estimations. Impact on value added and employment[1]



Source: Authors' own elaborations (micro-econometric model).
Notes: (1) Estimation of the effect of a credit shortfall = 1% of total credit to NFCs, one year ahead, in percentage on the level of real variables, ceteris paribus. The bars display 5 – 95 per cent confidence intervals. Estimation period 2014Q1-2019Q2.

It is also important to highlight that the multipliers derived from the models may differ substantially across the jurisdictions included in the sample. This does not only reflect the special features of each domestic banking sector as well as the overall legal and institutional framework, but also the degree of coverage of the banks included in the estimation, compared to the overall size of domestic banking sector.[25]

Connecting the dots: the impact of a bank failure on the real economy

The final goal of the proposed methodology is achieved by multiplying the credit shortfall potentially triggered by the failure of a given bank with the relevant multiplier. This combination of Step 1 and Step 2 is shown in Table 3.2., which gauges the macroeconomic impact of the failure of a medium-sized Significant Institution in case it would fail abruptly. The table focuses on two types of real economy multipliers: the FAVAR model estimate in terms of GDP (four quarter-ahead), and the micro-econometric model estimate in terms of value added, four quarter-ahead. Table 3.2 also illustrates the range of the available estimations and the uncertainty surrounding these estimations.

[25] For instance, in case of Germany, the multiplier might be underestimated, as the banks covered in the sample represent in terms of assets less than 60 per cent of the overall domestic banking sector. As of end- 2018, Germany's banking system comprises three pillars — private commercial banks, public-sector banks, and cooperative banks — distinguished by the legal form and ownership structure. The private commercial banks represent the largest segment by assets, accounting for 40 per cent of total assets in the banking system. The public banking sector comprises savings banks (Sparkassen), Landesbanken, and DekaBank, which acts as the central asset manager of the Savings Banks Finance Group, representing 26 per cent of total banks' assets. The cooperative sector consists of 875 cooperative banks (Volks- und Raiffeisenbanken) and one central cooperative bank (DZ Bank AG). It accounts for 50 per cent of institutions by number and 18 per cent of total bank assets.

Table 3.2. Real economic impact of the failure of a medium-sized bank[1] – illustrative results

(Average "Significant" bank (non-OSII). Impact through credit shortfall to NFCs. Data at 31.12.2018)

	(a) Step 1:	(b) Step 2: multipliers		(c) Impact on real economy	
	Credit shortfall (BSI, benchmark)	**Macro approach** (GDP)	**Micro approach** (Value added)	**Macro approach** (GDP)	**Micro approach** (Value added)
	(a)	(b.1)	(b.2)	(c.1 = a*b.1)	(c.2 = a*b.2)
Austria	**0.07**	**-1.04**	**[n.a.]**	**-0.07**	**[n.a.]**
		[-9.75 8.27]	*[n.a.]*	*[-0.68 0.58]*	*[n.a.]*
Germany	**0.06**	**-2.14**	**-0.16**	**-0.13**	**-0.01**
		[-6.51 5.17]	*[-0.57 0.25]*	*[-0.39 0.31]*	*[-0.03 0.01]*
Spain	**0.74**	**-0.48**	**-0.14***	**-0.36**	**-0.11***
		[-8.20 7.20]	*[-0.28 0.00]*	*[-6.07 5.33]*	*[-0.21 -0.00]*
Italy	**1.39**	**-1.17**	**-0.52****	**-1.63**	**-0.72****
		[-6.74 3.65]	*[-0.96 -0.07]*	*[-9.37 5.07]*	*[-1.34 -0.10]*

Source: Authors' own elaboration.

Notes: (1) For the multipliers from both models, the estimates denote the impact on the level of GDP or value added in percentage, one year ahead. Values in square brackets report the confidence intervals for the estimates (5-95 per cent). Stars display statistical significance at 10 (*), 5 (**) or 1 (***) per cent level.

The table suggests that the abrupt failure of an average mid-sized Significant Institution triggers an impact that is systematically lower if estimated in terms of valued added, through the micro-econometric approach, rather than in terms of GDP through the FAVAR model. Moreover, in terms of GDP, the average impact is lowest for Austrian banks, and highest for Italian banks.

Is the estimated impact of a bank failure relevant?

In order to gauge its relevance, the estimated impact on real economy variables is compared to threshold values, derived from the historical distribution of the real economy variables. The example provided here benchmarks the estimated GDP impact from the FAVAR model against historical real GDP growth. Table 3.3. presents a traffic light approach by setting possible thresholds for the real GDP quarterly growth, which can provide guidance to resolution authorities in assessing the relevance of the estimated outcomes. This approach identifies threshold values which differentiate between a green area (mild impact of a bank failure on real economy), a yellow area (significant impact, to be further assessed), and a red area (severe impact, to be carefully considered). The yellow area implies a reduction in output growth within the 25 per cent of the worst cases over the sample period (in our case, 1995Q1-2019Q4), but milder than the worst 10 per cent of cases, while the red area captures the worst 10 per cent of cases. The benchmark is primarily based on the time series at country level; however, since the past performances of heterogeneous countries could lead to assess differently otherwise similar outcomes, an European-level benchmarking can be also employed.[26]

[26] European-wide time series might display different behaviors than national time series: e.g., a more aggregate time series tends to be less volatile than its country components. Therefore, benchmarking against European time series should be considered as a complementary information to baseline the national benchmarking.

Table 3.3. Thresholds values, Real GDP growth[1]

		GDP impact from the bank failure is…		Memo Item:
		Lower than…	*Higher than…*	*Average GDP quarterly growth 1995Q1-2019Q4 (per cent)*
EU average	Green Area		-0.04	
	Yellow Area	-0.04	-0.65	*0.38*
	Red Area	-0.65		
Austria	Green Area		0.20	
	Yellow Area	0.20	0.00	*0.45*
	Red Area	0.00		
Germany	Green Area		0.00	
	Yellow Area	0.00	-0.34	*0.34*
	Red Area	-0.34		
Spain	Green Area		0.31	
	Yellow Area	0.31	-0.19	*0.53*
	Red Area	-0.19		
Italy	Green Area		-0.10	
	Yellow Area	-0.10	-0.48	*0.14*
	Red Area	-0.48		

Source: Authors' own elaboration on Eurostat
Notes: (1) Quarterly GDP growth in percentage, based on quarterly Eurostat data, 1995Q1-2019Q4. GDP is defined as: "GDP and main components (output, expenditure and income)" Eurostat item: [namq_10_gdp].

For example, the table suggests that, according to the historical data of the European (Eurozone, EU-19) GDP time series, the failure of a bank triggering an estimated reduction of 0.30 per cent of GDP would be classified in the yellow area, because this area includes GDP growth rates ranging from -0.04 to -0.65 per cent. By contrast, the same estimated impact would fall in the red area if benchmarked against the national Austrian time series, because, according to Austrian GDP growth rate time series, all negative impacts are in the red zone (i.e. below 0 per cent). At the same time, the estimated impact should be assessed against an average quarterly growth of Austrian GDP of 0.45 per cent since 1995 and the predicted growth rate, absent the bank failure. Finally, it has to be highlighted that, according to national time series, the same estimated impact (-0.30 per cent of GDP) of the failure of a Spanish bank would also be in the red area as for an Austrian bank, while for a German or an Italian bank it would be classified in the yellow area.

The application of the traffic light approach to the estimated impact on real GDP in each of the countries included in the sample allows assessing the materiality and severity of the estimated impact of a bank failure. To this end, some considerations are reported in Table 3.4. The first row in this table reports the estimated impact of the failure of an average significant bank, as per column "c.1 – macro approach" in table 3.2. It has to be noted that the following considerations are for illustrative purpose only as the point estimates are often not statistically significant at common significance levels.

For example, by adopting the country-specific traffic-light approach, the abrupt failure of a mid-sized Significant Institution in the sample countries would trigger a loss in terms of GDP which falls within a yellow ("attention") or a red ("severe impact") area. Furthermore, table 3.4 shows, for instance, that in Germany 18.1 per cent of quarters (yellow area), since 1995, showed a worse GDP change than the one potentially triggered by the failure of an average significant bank. In Austria, Spain and Italy, according to the country-specific time series, the estimated impact would fall in the red area: Italy has experienced the same event or worse only 1.6 per cent of times, while Austria and Spain 9.8 and 7.9 per cent of times respectively. An additional measure for assessing the severity of an impact would be its distance from the historical mean in terms of standard deviation, which is also displayed in the table 3.4. In Austria and Germany, the estimated impact is less than one standard deviation below the average growth rate of real GDP, while, by contrast, this distance amounts to over two standard deviations in Italy and, around one and half standard deviation in Spain. Finally, complementing the analysis with further information by considering also the historical performances as well as most recent economic forecasts, the estimated impact of a bank failure would be even more serious in countries – like Italy – characterised by weaker past performances in terms of historical means and lower growth expectations, according to the most recent official forecasts.

Table 3.4. Appraising the real economic impact of the failure of a medium-sized bank[1]

(Average "Significant" bank (non-OSII). Impact through credit shortfall to NFCs. Data at 31.12.2018)

	Austria	Germany	Spain	Italy
Real GDP estimated impact, SI bank[2]	**-0.07**	**-0.13**	**-0.36**	**-1.63**
Traffic light approach:				
- EU19 time series	Yellow	Yellow	Yellow	Red
- Country-specific time series	Red	Yellow	Red	Red
Frequency of worse outcomes[3]	9.8%	18.1%	7.9%	1.6%
(Impact – average)/ standard deviation	0.9	0.6	1.4	2.6
Historical quarterly mean	0.4%	0.3%	0.5%	0.1%
Country GDP growth:[4]				
- 2020	-7.4%	-5.0%	-11.0%	-8.8%
- 2021 (forecast)	+2.0%	+3.2%	+5.6%	+3.4%
- 2022 (forecast)	+5.1%	+3.1%	+5.3%	+3.5%

Source: Authors' own elaboration on own, Eurostat, and EC data.

Notes: (1) For the multipliers from both models the estimates denote the impact on the level of real GDP or value added in percentage one year ahead. - (2) Estimated impact of the failure of an average SI, non-OSII bank (four quarter ahead IRF from the FAVAR model. See section 2). - (3) Frequency of GDP quarterly variations in the country worse than the estimated impact from the bank failure, 1995-2019. - (4) European Commission's estimates and annual forecast as at February 2021.

4. Conclusions

This paper aims at providing a concrete contribution to the ongoing debate about how to perform the Public Interest Assessment, which is required by the European regulatory framework in both the resolution planning phase and at the time a bank is failing or likely to fail. We assess the possible impact of a bank failure on financial stability by focussing on the credit channel, i.e. the harm to economic growth that could stem from the temporary credit shortfall caused by the abrupt closure of a lender. We implicitly assume that a resolution of the lender would minimise the repercussion on its lending function. Since the impact on the economy is assumed to stem from a temporary credit shortfall, the impact itself is to be considered of a temporary, rather than permanent, nature.

In designing this methodology, we aim at introducing a feasible approach, applicable to every bank under the remit of the Single Resolution Mechanism (SRM) in a harmonised way across different jurisdictions. The methodology entails a first step, whereby the potential credit shortfall from the abrupt closure of the lender is quantified leveraging EU-harmonised banking databases. In a second step, we estimate the country-specific impact of any given credit shortfall onto real economic variables, such as GDP, value added or total employment. This second step exploits either a Factor Augmented Vector Autoregressive (FAVAR) approach or a micro-econometric model. Once the economic impacts of a specific bank failure are estimated, appropriate reference values are provided to benchmark the economic relevance of the estimated outcomes.

We find that such a harmonised method can be applied consistently across the Banking Union, and that it will become more robust as soon as more granular and longer time series become available. Moreover, we simulate the application of this methodology to a sample of EU Member States, showing that failures of similar banks in different countries display heterogeneous impacts on the domestic real economy. This is true both in absolute terms and when we benchmark this quantitative impact against the historical performance of the relevant economy in past decades.

For mid-sized ("grey area" or "middle class") banks, the implementation of this common analytical framework could provide useful insights to reduce the uncertainty on whether resolution is in the public interest, i.e. an assessment of whether the failure of the institution would endanger financial stability via a significant adverse impact on the real economy. The proposed framework has the advantage of being highly flexible, e.g. it can be easily adapted to estimate regional (rather than national) impacts.

At the same time, the limits of such an approach should be acknowledged. First, the credit channel could be analysed more in depth, e.g. leveraging more granular data or longer time series or databases, which are expected to become available in the future, also to account more explicitly for the possible cyclical dimension of the estimated credit multipliers. Second, the credit channel is only one of the channels at work from a bank failure to the overall financial stability. Therefore, other channels are worth being investigated, such as the confidence channel, i.e. the general loss of confidence that a sudden bank failure could trigger. Finally, when running a PIA, quantitative considerations are to be complemented by qualitative elements and expert judgment, as appropriate.

References

Alfaro, L., M. Garcìa-Santana, E. Moral-Benito (2018), “Credit supply shocks, network effects, and the real economy”, Harvard Business School Working Papers 18-052.

Aliano, M., M. Lo Cascio (2015), “The potential evolution of the supply of credit to the productive chain: A focus on Italy and the regional Sardinian economy”, Contributions to Economics, 214.

Altavilla, C., D. Andreeva, M. Boucinha, S. Holton (2019), “Monetary policy, credit institutions and the bank lending channel in the euro area”, Occasional Paper Series 222, European Central Bank.

Amiti, M., D.E. Weinstein (2018), “How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data”, Journal of Political Economy 126, 525–587.

Arias, J.E., J.F. Rubio-Ramírez, D.F. Waggoner (2018), “Inference based on structural vector autoregressions identified with sign and zero restrictions: Theory and applications”, Econometrica 86, no. 2 (2018): 685-720.

Ashcraft, A.B. (2005), “Are banks really special? New evidence from the FDIC-induced failure of healthy banks”, American Economic Review, 95(5), 1712–1730.

Baas, T., Schrooten, M. (2006), “Relationship banking and SMEs: A theoretical analysis”, small business economics 27, 127–137. https://doi.org/10.1007/s11187-006-0018-7.

Bai, J., N. Ng (2002) "Determining the number of factors in approximate factors models” Econometrica 70(1), 191-221

Barnett, A., R. Thomas, (2013), “Has weak lending and activity in the United Kingdom been driven by credit supply shocks?”, Bank of England working papers 482.

Barone, G., G. De Blasio, S. Mocetti (2018), “The real effects of credit crunch in the great recession: Evidence from Italian provinces”, Regional Science and Urban Economics 70, 352–359.

Blanchard, O.J., L. Katz (1992), “Regional Evolutions”, Brookings Paper on Economic Activity 1, 1-17.

BCBS - Basel Committee on Banking Supervision (2011), “The transmission channels between the financial and real sectors: a critical survey of the literature”, Working Paper No. 18.

Beck, T., S. Da-Rocha-Lopes, A.F. Silva (2018), “Sharing the pain? Credit supply and real effects of bank bail-ins”, CEPR Discussion Papers, 12058.

Bernanke, B., J. Boivin, P. Eliasz (2005), “Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach”, The Quarterly Journal of Economics, 120(1):387.

Berton, F., S. Mocetti, A.F. Presbitero, M. Richiardi (2018), Banks, Firms, and Jobs, Review of Financial Studies 31, 2113-2156.

Boot, A., A.V. Thakor (2000), “Can relationship banking survive competition?”, Journal of Finance, 55, 679-713.

Budnik K., P. Bochmann (2017), “Capital and liquidity buffers and the resilience of the banking system in the euro area”, ECB working paper No 2120, December.

Budnik K., M. Affinito, G. Barbic, S. Ben Hadj, E. Chretien, H. Dewachter, C. Isabel Gonzalez J. Hu, L. Jantunen, R. Jimborean, O. Manninen, R. Martinho, J. Mencia, E. Mousarri, L. Naruševičius, G. Nicoletti, M. O’Grady, S. Ozsahin, A.R. Pereira, J. Rivera-Rozo, C. Trikoupis, S. Velasco, F. Venditti (2019), “The benefits and costs of adjusting bank capitalisation: evidence from euro area countries”, ECB working paper No 2261, April.

Calomiris C.W., J.R. Mason (1994), “Contagion and bank failures during the Great Depression: The June 1932 Chicago banking panic”, NBER Working Paper Series, Working Paper No. 4934.

Covi, G., M. Montagna, G. Torri (2019), “Economic shocks and contagion in the euro area banking sector: a new micro-structural approach”, ECB, Financial Stability Review, 1.

Degryse, H., O. De Jonghe, S. Jakovljević, K. Mulier, G. Schepens, (2018), “Identifying credit supply shocks with bank-firm data: methods and applications”, Journal of Financial Intermediation.

Detragiache, E., P. Garella, L. Guiso, (2000), “Multiple versus single banking relationships: Theory and evidence”, The Journal of Finance, 55(3), 1133-1161.

ECB (2019), "Assessing the systemic footprint of euro area banks", in Financial stability review, European Central Bank, November.

Eickmeier, S., W. Lemke., M.G. Marcellino (2011), "The changing international transmission of financial shocks: evidence from a classical time-varying FAVAR", Journal of the Royal Statistical Society, Series A, 2015, vol. 178, issue 3, 493-533.

Finanstilsynet (2017), Main principles for resolution of small and medium-sized banks and determination of minimum requirements for own funds and eligible liabilities (MREL) – discussion paper.

Fukuda, S.I., S. Koibuchi (2006), "The impacts of "shock therapy" on large and small clients: Experiences from two large bank failures in Japan", The Japanese Economic Review 57, 232–256.

Girardi, A., M. Ventura, P. Margani (2018), "An indicator of credit crunch using Italian business surveys", MPRA Paper 88839, University Library of Munich, Germany.

Greenstone, M., A. Mas, H. Nguyen (2019), "Do credit market shocks affect the real economy? Quasi-experimental evidence from the Great Recession and `normal' economic times", American Economic Journal, Economic Policy, Vol. 12, No. 1, February 2020, 200-225)

Guler, O., Mariathasan, M., Mulier, K., Okatan, N. (2019), "The real effects of credit supply: Review, synthesis, and future directions", MPRA Paper No. 96542, 1 October 2019.

Hoggarth, G., R. Reis, V. Saporta (2002), "Costs of banking system instability: Some empirical evidence", Journal of Banking & Finance 26 (2002) 825–855.

Hristov, N., O. Hülsewig, T. Wollmershäuser, (2012), "Loan supply shocks during the financial crisis: Evidence for the Euro area", Journal of International Money and Finance, 31(3), 569-592.

Kupiec, P. H., C. D. Ramirez (2013), "Bank failures and the cost of systemic risk: Evidence from 1900 to 1930", Journal of Financial Intermediation, 22 (3), 285-307.

Lastra R.M, C.A. Russo and M. Bodellini (2019), "Stock take of the SRB's activities over the past years: What to improve and focus on?", Directorate-General for Internal Policies of the Union, Economic Governance Support Unit (EGOV) -PE 634.392 – March.

Lopez, P. (2015). "Rankings of bank vulnerability and systemicity." Mimeo.

Ongena, S., D.C. Smith (2000), "Bank relationships: A review", in Harker P. and S.A. Zenios (Eds.), "The performance of financial institutions", Cambridge University.

Petersen, M.A., R.G. Rajan (1995), "The effect of credit market competition on lending relationships", The Quarterly Journal of Economics, 110 (2), 407-443.

Presbitero, A.F., G.F. Udell, A. Zazzaro (2012), "The home bias and the credit crunch: A regional perspective", Mo.Fi.R. Working Papers 60, Money and Finance Research group (Mo.Fi.R.) - Univ. Politecnica Marche - Dept. Economic and Social Sciences.

Puri, M., J. Rocholl, S. Steffen (2011), "Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects", Journal of Financial Economics 100.3 (2011): 556-578.

Ramirez, C. D., P.A. Shively (2012), "The effect of bank failures on economic activity: evidence from US states in the early 20th century", Journal of Money, Credit and Banking, 44(2-3), 433-455.

Restoy F., R. Vrbaski. and R. Walters. (2020), "Bank failure management in the European banking union: What's wrong and how to fix it", Occasional Paper, No 15, July.

Veron N. (2019), "Taking stock of the Single Resolution Board", Directorate-General for Internal Policies of the Union, Economic Governance Support Unit (EGOV), PE 634.393 – March.

List of abbreviations

BRRD	Bank Recovery and Resolution Directive
BSI	Balance Sheet Items
CF	Critical Function
Corep	Common Reporting
EBA	European Banking Authority
ECB	European Central Bank
EONIA	Euro Overnight Index Average
FAVAR	Factor Augmented-Vector Autoregression
FDIC	Federal Deposit Insurance Corporation
Finrep	Financial Reporting
FOLTF	Failing or Likely to Fail
GDP	Gross Domestic Product
HHs	Households
LSI	Less Significant Institutions
NACE	Nomenclature of economic activities in the European Community
NCB	National Central Bank
NFCs	Non-financial corporations
NIP	Normal insolvency proceedings
NPL	Non-performing Loan
NRA	National Resolution Authority
NUTS	Nomenclature of Territorial Units for Statistics
OSII	Other Systemically Important Institution
PIA	Public Interest Assessment
ROA	Return on Assets
ROE	Return on Equity
RWAs	Risk Weighted Assets
SI	Significant Institution
SME	Small and medium enterprise
SRB	Single Resolution Board
SRM(R)	Single Resolution Mechanism (Regulation)
SSM	Single Supervisory Mechanism
VA	Value Added
VAR	Vector AutoRegression

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