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SHOULD THE CCYB BE ENHANCED WITH A SECTORAL DIMENSION? THE CASE OF ITALY

by Roberta Fiori* and Claudia Pacella**

Abstract

The paper investigates whether there is sufficient empirical support in Italy for the introduction of a sectoral countercyclical capital buffer (CCyB) in the macroprudential framework. We study the sectoral decomposition of the credit-to-GDP gap over the period 1990Q1-2017Q2. Overall, our results suggests that a sectoral CCyB could be a useful addition to the macroprudential framework as both the timing for activation and the size of the capital buffer can differ when accounting for the sectoral dimension of the credit-to-GDP gap. We find that the synchronicity of sectoral credit cycles decreases as we move from a two-sector to a six-sector decomposition. Moreover, the contribution of sectoral cycles to systemic stress, as measured by the system-wide new bad debt rate, as well as the prudential requirements associated with their risk exposure differ quite significantly. While exuberance in the non-real-estate related segment of corporate lending is usually followed by a surge in systemic stress, exuberance in the real-estate related segment of business lending does not.

JEL Classification: E32, G01, G21, G28.

Keywords: credit cycle, sectoral decomposition, synchronicity, cyclical systemic risk.

Contents

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1. Introduction[1]

The paper investigates whether the countercyclical capital buffer (CCyB) should be enhanced with a sectoral dimension. In principle, the introduction of a sectoral CCyB would add flexibility to the macroprudential toolkit, to the extent that it allows sectoral imbalances (e.g. in the real estate sector) to be addressed without raising the cost of credit in other sectors. If cyclical systemic risks are building up in a specific credit segment, the use of a broad-based CCyB could be inefficient. Should the largest contribution to the credit-to-GDP gap come from the household sector, for example, a broad-based CCyB would unduly penalize business lending as the capital buffer would be imposed on total risk-weighted assets. A more targeted tool, addressing credit developments in the household and corporate sectors separately, would be as effective as the broad-based CCyB but more cost-efficient, as it would entail fewer unintended consequences. Moreover, a sectoral CCyB would complement existing sectoral tools without affecting risk weights and risk parameters.

However, the introduction of a sectoral CCyB in the macroprudential toolkit would also have some drawbacks. A key issue concerns the trade-off between the degree of granularity and the robustness to elusion: in general, the more granular the tool, the more it is prone to elusion. Furthermore, sectoral CCyBs would pose operational challenges in their design and calibration (e.g. definition of the relevant sectors) and in their interaction with the broad-based CCyB (i.e. whether they should be considered a substitute or a complement). Finally, the operational burden for banks would increase, as would the work of the supervisor.

As a result, the decision whether or not to introduce sectoral buffers should rest primarily on empirical considerations. This is the aim of the paper. By focusing on the sectoral dimension of the data, it adds empirical evidence on the intertemporal relationships among sectoral credit cycles as well as on their causality. Moreover, it sheds lights on the contribution of sectoral credit cycles to the build-up of systemic credit risk by considering a pre-defined number of credit segments that are relevant for policymaking. This evidence is important for the issue at hand because the usefulness of a sectoral CCyB clearly depends on the shape of sectoral credit cycles. If they were of the same amplitude and fully synchronized, there would clearly be no reason to introduce sectoral CCyBs.

The first part of the paper analyses the degree of synchronization between different sectoral credit cycles in Italy. The credit cycle within each sector is measured in line with the approach developed by the Bank of Italy to implement a broad-based CCyB (Alessandri et al., 2015). The analyses range from a two- to a six-sector decomposition of the overall credit cycle, which is the maximum level of granularity that can be achieved given the length of the available time series of sectoral data. The rationale behind a sectoral decomposition of the cycle is threefold. First, aggregate cycles can mask cross-sectoral variation. Second, the contribution of sectoral cycles to systemic stress, as well as the prudential requirements associated with their risk exposure, could differ quite significantly. Third, some sectors are by nature less exposed to cyclical fluctuations than others.

[1] We thank Marcello Bofondi, Fabio Busetti, Francesco Piersante, and especially Paolo Angelini for their helpful comments and suggestions. This work was begun within the Basel Committee's Research Task Force workstream on sectoral CCyB (BCBS, 2019), whose support is gratefully acknowledged. The views expressed are those of the authors and do not involve the responsibility of the Bank of Italy or of the Eurosystem.

Once sectoral credit cycles have been identified, cycle synchronization is assessed by various measures.

The second part of the paper focuses on the contribution of sectoral credit cycles to systemic credit risk in Italy. As macroprudential policy has a system-wide perspective, cyclical systemic risk assessments should focus on the sectors that might entail risks to the stability of the broader financial system.

The main conclusions of the paper are the following. The credit cycle used as a reference guide for policy decisions on the broad-based CCyB does indeed mask significant cross-sectoral variation. The degree of synchronicity across sectoral cycles decreases as we move from a two-sector decomposition of the credit-to-GDP gap (households versus non-financial firms) to a six-sector decomposition (i.e. loans for house purchase, consumer credit, loans to real-estate-related medium and large enterprises (MLE-RE), loans to non-real-estate-related medium and large enterprises (MLE-nonRE), loans to real-estate-related small enterprises (SE-RE) and loans to non-real-estate-related small enterprises (SE-nonRE). Moreover, the contribution of sectoral imbalances to systemic stress in Italy, as measured by the system-wide new bad debt rate, also differs quite substantially, as does the prudential requirement associated with sectoral exposures. Overall, these results suggest that a sectoral CCyB could be a useful addition to the macroprudential framework to the extent that both the activation timing and the capital buffer size can differ when accounting for the sectoral dimension of the credit-to-GDP gap.

The paper is structured as follows: Section 2 gives an overview of the relevant literature; Section 3 shows the key features of the financial cycle in Italy; Section 4 illustrates the prudential requirement and credit risk by sector of exposure; Section 5 describes the data and the methodology used to extract sectoral cycles and measure their synchronization; Section 6 highlights the main findings behind the sectoral decomposition of the credit cycle; Sector 7 focuses on the contribution of sectoral imbalances to systemic stress; and Section 8 illustrates the implications of the analyses for CCyB policy decisions. Section 9 concludes.

2. Literature review

There is a large strand of the literature calling for a sectoral dimension of systemic risk assessment in order to capture the interactions and interlinkages among sectors. Systemic risk propagation across sectors can materialize through a number of complex channels: direct links between firms such as trade credit, and indirect links such as common exposure to macroeconomic fundamentals. Fiori et al. (2009) and Jiménez and Mencía (2007) model historical default rates grouped by sectors of economic activity. In these models, macroeconomic variables represent the systematic risk component, while sector-specific variables represent the idiosyncratic risk component. Both studies identify agriculture, manufacturing, construction and trade as 'cyclical' sectors, while mining and quarrying and utilities are 'idiosyncratic'. The main contribution of Fiori et al. (2009) is a distinctive approach to accounting for contagion across sectors after controlling for the dependency of sectoral default risks on the macro-financial environment. The paper shows that sectoral default risk is not entirely explained by the business cycle; part of default correlation stems from the existence of sectoral interdependence (e.g. business links such as supply chains) which could amplify the riskiness of loan portfolios via contagion.

Sectoral or geographical factors may also influence the default risk of otherwise unrelated firms (Lucas, 1995). It is therefore better to model default risk as driven by multiple risk factors, as opposed to assuming a single risk factor driving correlations across borrowers (Gordy, 2003).
The key features of sectoral risk and its response to common macroeconomic shocks are also fairly heterogeneous. Sectoral risk relationships and their dynamics have been analysed using market-based indicators in Alves (2005) with a VAR approach and in Castren and Kavonius (2009) using network analysis. Their results highlight important cross-sectoral dynamics, in addition to the systemic impact generated by macroeconomic variables. Neglecting the sectoral dimension in credit risk modelling might thus result in capital provisions being insufficient to buffer potential losses, with major implications for financial stability and policy decision-making. Indeed, sectoral risks, in the sub-segments of both the household and the corporate sectors, have the potential to adversely affect bank stability as well as the broader economy (Alves, 2005; Jiménez and Mencía, 2007; Castren and Kavonius, 2009; Koetter and Poghosyan, 2010; Acemoglu et al., 2012; Jordà et al., 2014).

Duellmann and Masschelein (2007) estimate the potential impact of sector concentration on economic capital using German data. Credit risk is measured via a structural multi-factor model using Monte Carlo simulations. Saldías (2013) addresses the importance of heterogeneity across corporate sectors in the euro area in terms of risk determinants and transmission taking into account both the cross-sectional dimension and the time-series dimension of risk. The paper shows that neglecting this heterogeneity by focusing only on macro-financial determinants of risk would be misleading in terms of overall credit risk management, financial stability analysis, and policy decisions. Accornero et al. (2017) outline a framework for measuring credit risk in banks' exposures to non-financial firms which accounts for the role played by sectoral risk factors. The paper adds new evidence on credit risk indicators based on portfolio theory by means of a structural multi-factor model that captures the dependency of firms' joint default probabilities on their sectoral affiliation.[2] The authors show that accounting for sectoral risk factors matters. Indeed, credit risk, as measured by expected and unexpected losses, differs quite substantially across sectoral exposures. Probabilities of default display greater variability than recovery rates. Unexpected losses also display great sectoral variability and are positively associated with the cyclical nature of the sectors.[3] Taken together, these findings advocate the use of a multi-factor model to spot credit risk in particular sectors, an issue that is gaining momentum in macroprudential analysis. Another contribution of the paper is the proposal of a measure for the systemic risk relevance of sub-portfolios. This measure can help to identify the economic sectors that might play

[2] A structural multi-factor model, as prompted in Duellman and Masschelein (2007), is applied to the Italian economy using a granular firm-bank level dataset covering the credit exposure of Italian banks to non-financial firms, probabilities of default and loss-given default.

[3] For instance, exposures in the property sector (i.e construction) display a remarkably higher default risk compared with other sectors. Its contribution to the unexpected loss of Italy's aggregate corporate portfolio is also markedly higher than its share of debt.

a major role in the stability of the banking system in economic downturns, contributing more than others to potential losses.

Another strand of literature emphasises that, notwithstanding financial integration, in many countries financial cycles are not fully synchronized. Moreover, within each country credit to households and credit to non-financial corporations very often show quite different patterns (Meller and Metiu, 2017; Samarina et al., 2015; De Backer et al., 2016). This means that the credit cycle used as a reference guide for policy decisions on the broad-based CCyB could mask significant cross-sectoral variation and could lead to misleading signals. In the existing literature, however, the synchronization of sectoral credit cycles is assessed at a relatively higher aggregate level. In our paper, the disaggregation of sectoral credit cycles into different types of credit to households (e.g. mortgage credit versus consumer credit) and different corporate sectors provides further useful insights on the required level of granularity in cyclical systemic risk policy assessment.

Finally, the Basel Committee on Banking Supervision (BCBS, 2018) has reviewed the existing theoretical and empirical literature to shed light on whether the Basel III CCyB framework could be extended to a sectoral application. The review shows that there is a justifiable need for sectoral macroprudential tools and that a sectoral CCyB could be a useful complement to existing sectoral tools. However, both broad-based and sectoral countercyclical capital buffers remain largely untested and more empirical work is needed to assess their ability to achieve the intended objectives.

3. The Italian financial cycle

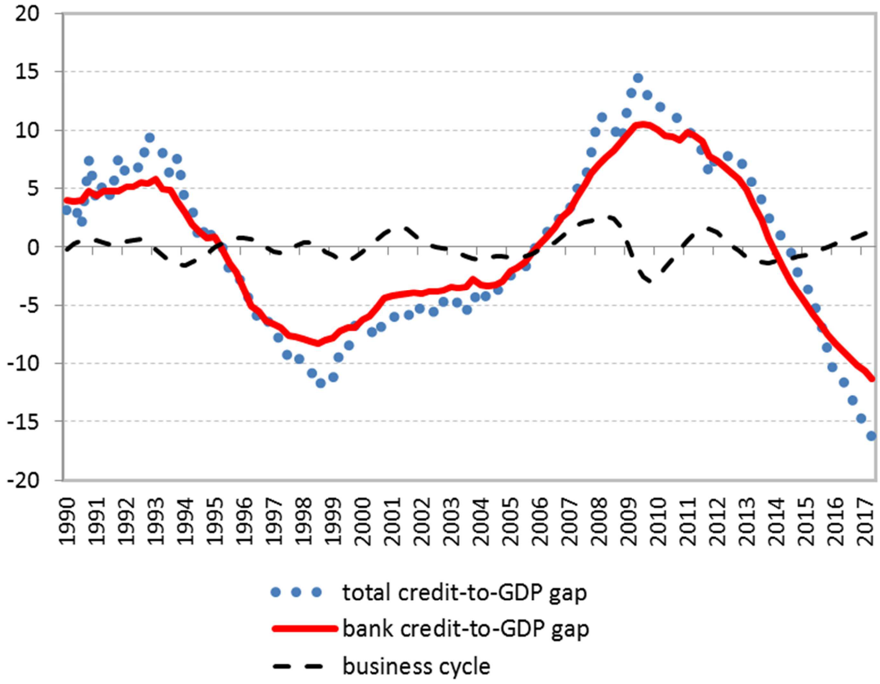
Monitoring credit developments is important for maintaining financial stability. The BCBS (2010) introduced a countercyclical capital buffer to protect the banking system and the economy from periods of excess credit growth. The gap between the credit-to-GDP ratio and its long-term trend was proposed as a measure of the financial cycle and as a reliable indicator of financial leverage.

In order to examine the main stylized features of the Italian financial cycle we therefore focus on the credit-to-GDP ratio and its gap. While the gap proposed by Basel III ('Basel gap') relies on a broad measure of credit to the private non-financial sector, we focus mainly on a narrow measure of the gap (i.e. bank-credit-to-GDP gap) for two reasons: first, because the financial cycle in Italy is mainly bank driven; second, because bank credit is a better predictor of financial stress than total credit (Alessandri et al., 2015). Previous studies on the Italian financial cycle (De Bonis and Silvestrini, 2014; Bartoletto et al., 2017; Bulligan et al., 2019) show that evidence for Italy is broadly in line with that for other advanced countries: financial cycles have a much longer duration than business cycles (Figure 1).[4]

[4] The Italian financial cycle shown in this picture differs slightly from the one used by the Bank of Italy to inform policy decisions on the CCyB rate because it is extracted on a shorter time period (1990Q1-2017Q2) in order to match the empirical evidence available at sectoral level, starting from 1990Q1.

Figure 1. The Italian financial and business cycle

(per cent)



Source: Bank of Italy. The financial cycle is measured by the credit-to-GDP gap, which is the deviation of the actual credit-to-GDP ratio from its long-term trend, as estimated by applying a two-sided HP filter with a smoothing parameter of 400,000. The business cycle is measured as the deviation of real GDP growth from its long-term trend by applying a two-sided HP filter with a smoothing parameter of 1,600.

While the length of the business cycle in Italy usually ranges from 2 to 8 years, the financial cycle lasts between 9 and 40 years. Moreover, swings in the financial cycle are more pronounced than those in the business cycle. Given that the length of the business cycle is much shorter than that of the financial cycle, real and financial cycles tend to be poorly synchronized and economic recessions do not usually coincide with downturns in the financial cycle. However, when the negative phases overlap, as happened in the recent financial crisis and in a few other cases in the past, the recession turns out to be deeper (Bartoletto et al., 2017).[5] In addition, consistently with the hypothesis of a financial accelerator mechanism (Bernanke et al., 1996), Bulligan et al. (2019) show that a joint trend-cycle decomposition for GDP and credit unveils significant feedback effects (measured as phase shifts) between the financial and business cycles in Italy. The joint trend-cycle decomposition suggests that the financial cycle Granger-causes the business cycle by amplifying its fluctuations. Therefore, policy tools must take the relationship between the financial and business cycles into account in order to be successful in containing risks in both the short and the long run.

In Italy, periods of credit expansion have often been followed by episodes of financial distress (De Bonis and Silvestrini, 2014). In our observation period, two peaks of the credit cycle are clearly visible: the first from 1990 to 1993 and the second in 2008-10. In the first half of the 1990s the

[5] While Bartoletto et al. (2017) did not find evidence that the credit cycle leads the business cycle in either medium- or short-run fluctuations, for short cycles they found some evidence that the business cycle leads the credit cycle. A causality analysis confirms that GDP Granger-causes credit in short cycles and that, when causality is significant, the probability of an upturn in credit increases in an expansionary phase.

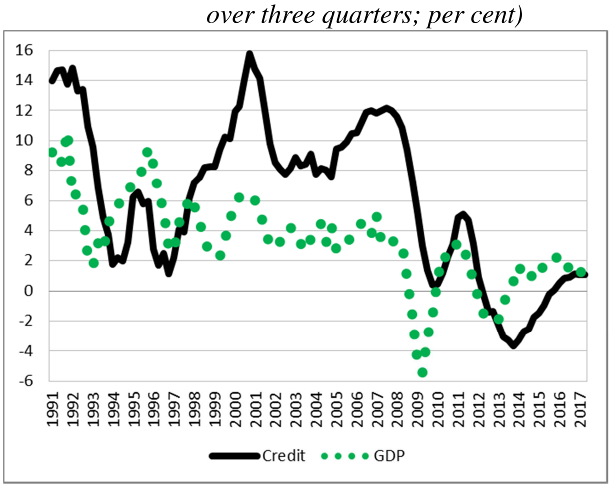
main southern Italian banks — all owned by general government and affected by allocative and cost inefficiencies — were hit by the 1992 financial crisis when Italy was forced to leave the European Monetary System. The consequences were very severe, especially because of the deep recession of 1992-93. The crisis of the southern banks was solved by fostering mergers, acquisitions and privatizations. The period 1993-2008 was marked by an initial sharp contraction in credit in 1993-96, a particularly fragile period for the Italian economy faced with the establishment of the Eurozone as well as a crisis linked to fiscal imbalance and the exchange-inflation relationship. This period also corresponds to another major reform of the banks' business model, namely the 1993 Banking Law (*Testo Unico Bancario*), which eliminated all distinction between short-term and long-term credit institutions and restored a universal banking model. Thanks to the major reforms introduced during the 1990s, the banking system succeeded in overcoming the difficulties, and in the following years credit grew at an average of 5 per cent per year. The 2008 peak referred to the phase of credit expansion, which lasted until the eve of the global financial crisis.

Looking at the latest data, bank loans to residents in Italy amount to 76 per cent of GDP. The proportion is close to the value recorded in 2008 and is 17 percentage points lower than the peak recorded in 2012.[6] Notwithstanding improvements in macro-financial conditions, the credit-to-GDP gap, i.e. the deviation of the ratio of bank lending to GDP from its long-term trend, is still markedly negative.

Figure 2. Nominal bank credit and GDP

Panel A. Nominal GDP and bank credit

(moving average of year-on-year growth rates over three quarters; per cent)

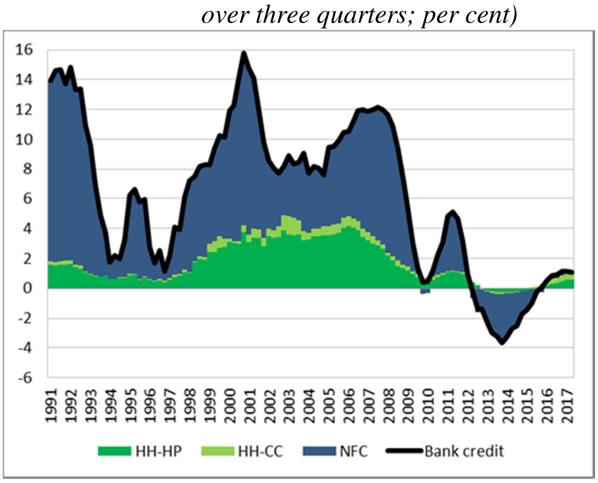


Source: Bank of Italy and Istat

Bank loans granted to households and non-financial corporations, net of bad debts.

Panel B. Bank credit by sector

(moving average of year-on-year growth rates over three quarters; per cent)



Source: Bank of Italy and Istat

Bank loans granted to households and non-financial corporations, net of bad debts; contributions to bank credit growth. The credit sectors are non-financial corporations (NFC); mortgage loans (HH-HP); and other consumer loans (HH-CC).

6 See the Bank of Italy's decision on the Countercyclical Capital Buffer (CCyB) rate for the first quarter of 2019: https://www.bancaditalia.it/compiti/stabilita-finanziaria/politica-macroprudenziale/ccyb-1-2019/index.html?com.dotmarketing.htmlpage.language=1

Bank credit to the non-financial private sector increased steadily from 1997 to 2008 (Figure 2, Panel A). After a short recovery in 2011-12, lending entered negative territory thereafter. Since 2016 it has remained subdued.

4. Prudential requirements and credit risk by sector of exposure

An important difference between the broad-based CCyB and a sectoral version of the tool is that in the former the additional capital requirement is imposed on total risk-weighted assets (RWA). Therefore, the additional resilience built up within the system through its activation accounts for the fact that the bursting of a bubble may lead to a general downturn, and neither the share of credit to total exposure nor its distribution across different credit segments plays a role. However, if cyclical systemic risks are building up in a specific credit segment, a sectoral CCyB could have a competitive advantage over a broad-based one as it allows the sectoral imbalance to be addressed without raising the cost of credit in other sectors. Applying additional buffer requirements only to the risky credit segment would minimize the potential negative effects on the supply of credit to other segments. This could be particularly desirable in situations where the build-up of sectoral imbalances is combined with low overall economic growth prospects. For instance, if cyclical risks are building up in the real estate sector, a broad-based CCyB would unduly penalize lending to non-financial corporations. In this situation, a more targeted tool would be as effective as the broad-based CCyB, but more cost efficient as it would entail fewer unintended consequences.

In order to gauge the different regulatory requirements associated with sectoral exposures, we compute their risk density as measured by the ratio between the associated risk-weighted assets and the corresponding exposure amount. It is worth noting that holding capital against RWA is consistent with the greater risk sensitivity of the regulatory framework. This risk sensitivity is meant to limit the incentives for banks to engage in excessive risk taking by requiring them to hold adequate capital to cover the underlying risks. Riskier portfolios usually translate into higher risk weights. Therefore, we also compare the prudential requirements with the riskiness of the corresponding exposure, as proxied by sectoral NPL ratios (based on stocks) and average default rates (based on flows). Not surprisingly, prudential requirements differ quite substantially across sectors. Moreover, the higher the credit risk originating from the sector, the higher will be the capital required to absorb unexpected losses. More specifically, exposures secured by immovable assets, such as loans for house purchase, have relatively low risk exposures and risk-weight density, partly thanks to the high share of loans backed by real guarantees. This is also the case for exposure to real-estate-related medium and large enterprises , which have a relatively low risk density compared with the underlying riskiness because of the high proportion of collateralized loans. Exposures to small enterprises instead have a relatively higher risk density (Table 1).

Table 1. Prudential requirement vis-à-vis credit risk indicators

(three-year average over the period 2014-16; per cent)

Credit segment	Share of total loans	NPL ratio (1)		Default rate (2)	RW Density (3)
		Gross	Net		
MLE-nonRE	40	22	12	2.7	44
MLE-RE	17	46	33	7.9	23
HH-HP	25	8	5	1.5	25
HH-CC	5	18	10	n.a.	15
SE	13	24	14	4.6	66

Source: Supervisory reporting and Central Credit Register. The credit segments are: real-estate-related medium and large enterprises, (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); mortgage loans (HH-HP); other consumer loans (HH-CC); and small enterprises (SE). (1) Stock of non-performing loans to total loans, gross and net of write-downs. (2) Ratio of new bad loans to outstanding loans (amount). (3) Ratio of risk-weighted assets to exposure amount. For this purpose MLE-nonRE includes corporate and SME corporate portfolios; MLE-RE includes corporate and SME corporate portfolios secured by immovable assets; and SE includes SME retail and 'other retail' portfolios, both secured and not secured by immovable assets.

5. Data and methodology

In line with the Basel framework, the credit-to-GDP ratio in quarter *t* for each sector *i* is calculated as:

$$\text{Credit-to-GDP ratio}_{it} = \frac{c_{it}}{\text{GDP}_t + \text{GDP}_{t-1} + \text{GDP}_{t-2} + \text{GDP}_{t-3}} \cdot 100$$

where GDP_t is nominal GDP[7] and c_{it} is a measure of nominal credit to sector *i* in quarter *t* over the period 1990Q1-2017Q2.[8] While the Basel gap mainly relies on a broad measure of credit to the private non-financial sector (i.e. total credit to the private non-financial sector), we focus on a narrow definition (i.e. bank credit-to-GDP ratio).

The credit-to-GDP ratio at sectoral level is compared with its long-term trend to check whether there is any indication that credit in a specific sector has grown to excessive levels relative to GDP. The gap in period *t* for each sector *i* is then calculated as the actual credit-to-GDP ratio for sector *i* minus its long-term trend.

[7] The ratio can be computed considering sectoral value added instead of GDP. Results on a sub-sample of sectors are broadly consistent (see Appendix 2).
[8] Data on credit are drawn from supervisory reporting, while data on nominal GDP and value added are from ISTAT.

To compute the gaps we apply a two-sided HP filter (Hodrick and Prescott, 1997)[9] with a smoothing parameter of 400,000, consistently with Alessandri et al. (2015) according to which the standard Basel gap, based on a one-sided HP filter, does not provide a reliable picture of the financial cycle in Italy. We also run different robustness checks by applying other filtering techniques in the frequency domain, such as the band pass filter à la Christiano and Fitzgerald (2003), which allows us to extract the cycle by isolating the medium-to-long-term frequencies, i. e. between 8 and 25 or 30 years (Drehmann et al., 2012). These different measures of the gap all give a very consistent picture of the Italian financial cycle.[10]

Our analyses span a two- to a six-sector decomposition of the credit cycle (Table 2). The two-sector decomposition distinguishes non-financial corporations (NFC) from households (HH). The definition of these two sectors is consistent with the one applied in the Bank of Italy, where the corporate sector includes producer households. The four-sector decomposition takes into account the purpose of loans by further splitting the NFC sector into two credit segments: real-estate-related non-financial corporations (NFC-RE), represented by construction firms and real-estate agencies, and non-real-estate-related non-financial corporations (NFC-nonRE). Moreover, loans to households are further split into loans for house purchase (HH-HP) and consumer credit (HH-CC). In the six-sector decomposition the corporate sector is further broken down by firm size into real-estate-related medium and large enterprises (MLE-RE), non-real-estate-related medium and large enterprises (MLE-nonRE), real-estate-related small enterprises (SE-RE), and non-real-estate-related small enterprises (SE-nonRE), in which small enterprises (SE) include producer households and small firms up to 20 employees, while MLE represents the rest of the corporate sector. The six-sector decomposition is the maximum level of granularity that can be achieved with sufficiently long time series of sectoral data.

[9] The HP filter is a standard tool used in macroeconomics to extract the trend (and the cycle) of a variable over time. While a one-sided HP filter uses, at each point in time, only information available up to that time to calculate the trend, the two-sided HP filter exploits all the information available up to the end of the sample period. The smoothing parameter is set at 400,000 to capture the long-term trend in the behaviour of the credit-to-GDP ratio, consistently with the recommentations of Basel III. Nevertheless, the HP filter does have drawbacks. First, the trend depends to some extent on the length of the time series and on the smoothing parameter. Second, it is subject to the end-point problem, which generates high uncertainty around the estimate of the trend at the end of the sample period.

[10] See Figure A1.1 in Appendix 1.

Table 2. Sectoral decomposition of the credit cycle

Two-sector decomposition		**Four-sector decomposition**		**Six-sector decomposition**	
NFC	Non-financial corporations, including producer households	**NFC-RE**	Real-estate-related non-financial corporations: construction and real-estate agencies	**MLE-RE**	Real-estate-related medium and large enterprises
				SE-RE	Real-estate-related small enterprises (producer households and small firms up to 20 employees)
		NFC-nonRE	Non-real-estate-related non-financial corporations	**MLE-nonRE**	Non-real-estate-related medium and large enterprises
				SE-nonRE	Non-real-estate-related small enterprises (producer households and small firms up to 20 employees)
HH	Consumer households	**HH-HP**	Loans for house purchase, i. e. mortgages	**HH-HP**	Loans for house purchase, i. e. mortgages
		HH-CC	Consumer credit	**HH-CC**	Consumer credit

To study the synchronization of expansion and contraction phases across credit segments, we map each sectoral credit cycle into a binary variable $B_{i,t}$ which takes the value 1 if the credit cycle is in a phase of expansion and -1 if it is in a phase of contraction.

Following Meller and Metiu (2017) we measure the average pairwise contemporaneous synchronization between the cycles of sectors *i* and *j* as follows:

$$\mu_{i,j} = \frac{1}{T}\sum_{t=1}^{T} B_{i,t}\, B_{j,t}$$

There are different ways to define the $B_{i,t}$ variable. We first consider the pairwise gap synchronization by defining $B_{i,t}$ in terms of deviations of credit from its long-run trend level:

$$B_{i,t} = \frac{c_{i,t}}{|c_{i,t}|} = \begin{cases} 1 & \text{if credit is above long run trend} \\ -1 & \text{if credit is below long run trend} \end{cases}$$

We then study the pairwise swing synchronization by considering the direction of changes:

$$\mathrm{B_{i,t}} = \frac{\Delta \mathrm{c_{i,t}}}{|\Delta \mathrm{c_{i,t}}|} = \begin{cases} 1 & \text{if credit is in upswing} \\ -1 & \text{if credit is in downswing} \end{cases}$$

In order to assess the lead/lag relationships of both measures, we also compute the average pairwise synchronization at different leads and lags h:

$$\mu_{\mathrm{i,j,h}} = \frac{1}{\mathrm{T}} \sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{B_{i,t}}\, \mathrm{B_{j,t+h}}$$

We consider a six-year window ($h = -24, \dots, 24$) to find the lead or lag where the degree of synchronization reaches its peak in absolute value. For every pair of sectors we keep a record of the following lead/lag:

$$\widehat{h_{i,j}} = \arg \max_{h=-24,\dots,24} |\mu_{i,j,h}|$$

corresponding to the highest degree of synchronization:

$$\hat{\mu}_{\mathrm{i,j}} = \mu_{\mathrm{i,j,\hat{h}}}$$

Finally, to assess the contribution of the sectoral imbalances to systemic credit risk we use as target variable the new bad debt rate at aggregate level. The new bad debt rate is derived from the Central Credit Register. Bad debts are exposures to debtors that are insolvent or close to insolvent. They have been annualized by dividing the sum of quarterly flows of new bad debts over the year to the average stock of outstanding loans in the corresponding year.

6. Sectoral decomposition of the Italian credit cycle: empirical evidence

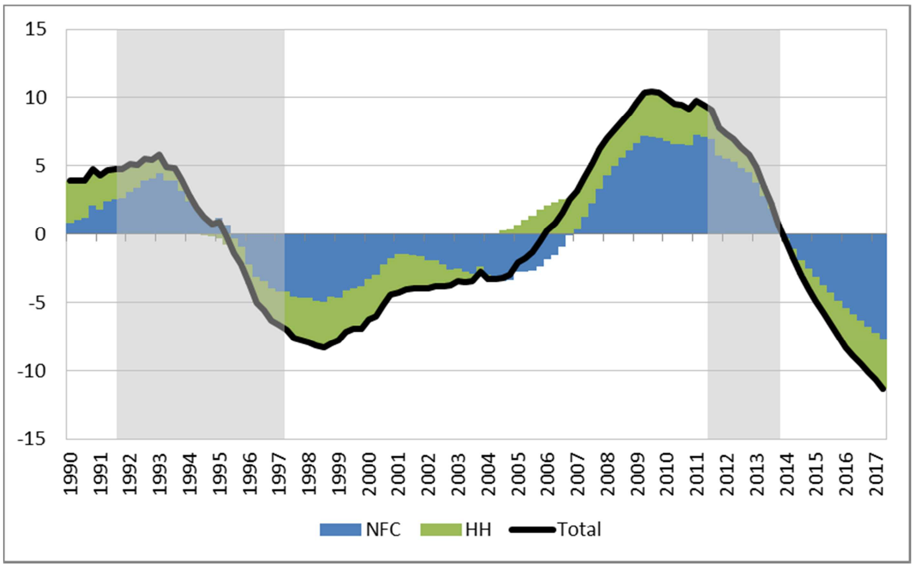
The sectoral decomposition of the credit cycle is analysed at different levels of granularity. By graphic inspection, the sectoral decomposition of the credit cycle highlights a certain degree of cross sectoral variation over the period 1990Q1-2017Q2. We start from a two-sector decomposition where the corporate sector is distinguished from the household sector (Figure 3, Panel A). We observe that the corporate sector (NFC) plays a major role in driving the credit cycle in Italy, especially during credit downturns. Grey shaded areas cover the two systemic banking crises that occurred in Italy during the period, as identified by Lo Duca et al. (2017). The first crisis started in 1990Q3 and ended in 1997Q4. It consisted in turbulence in the currency markets in connection with the Exchange Rate Mechanism (ERM) crisis, when the lira exited the ERM, and subsequent distress in the economy and in the banking sector. In the 1990s several banks in southern Italy – generally publicly owned and affected by allocative and cost inefficiencies – were severely hit by the crisis. The second episode started in 2008Q3 and ended in 2013Q4. Instability originated from tensions in the sovereign bond markets that affected the Italian economy through several channels (Neri and Ropele, 2015).The deterioration in sovereign creditworthiness made bank funding more costly and difficult to obtain; that translated into a higher cost of credit and gave rise to an outright reduction in the availability of loans.

Moving to a four-sector decomposition (Figure 3, Panel B), we note that the contribution of non-financial corporations with real-estate-related activities (NFC-RE) and those with non-real-estate-related activities (NFC-nonRE) are balanced overall, even though they are not fully synchronized, especially in the period 2000Q1-2002Q4 when the contribution of NFC-nonRE to the cycle was positive while that of NFC-RE remained negative until 2006Q1. Cross-sectoral variation further increases if we account for firm size (Figure 3, Panel C).The cycles driven by small enterprises tend to show an idiosyncratic pattern, most likely owing to their lower exposure to cyclical fluctuations.

Figure 3. Sectoral decomposition of the credit cycle

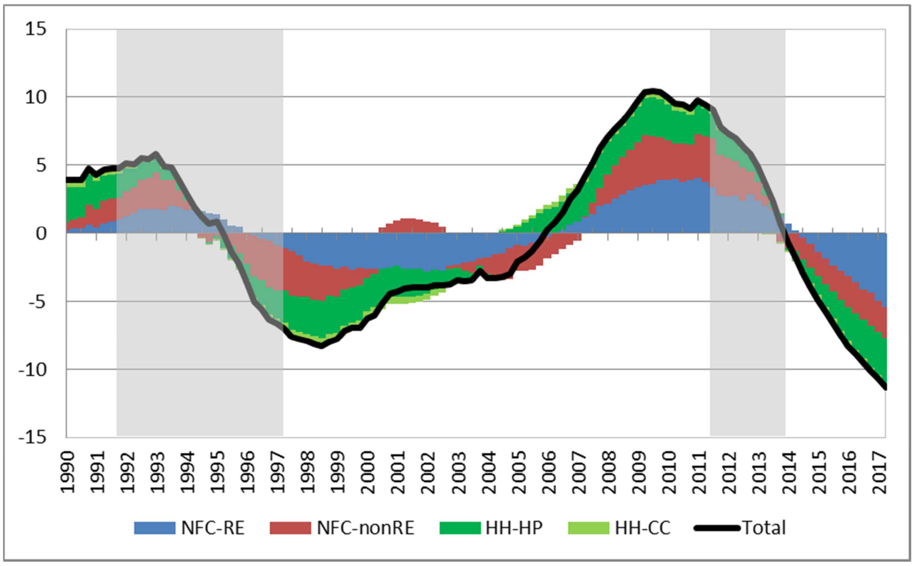
(per cent)

Panel A. Two-sector decomposition of the credit-to-GDP gap



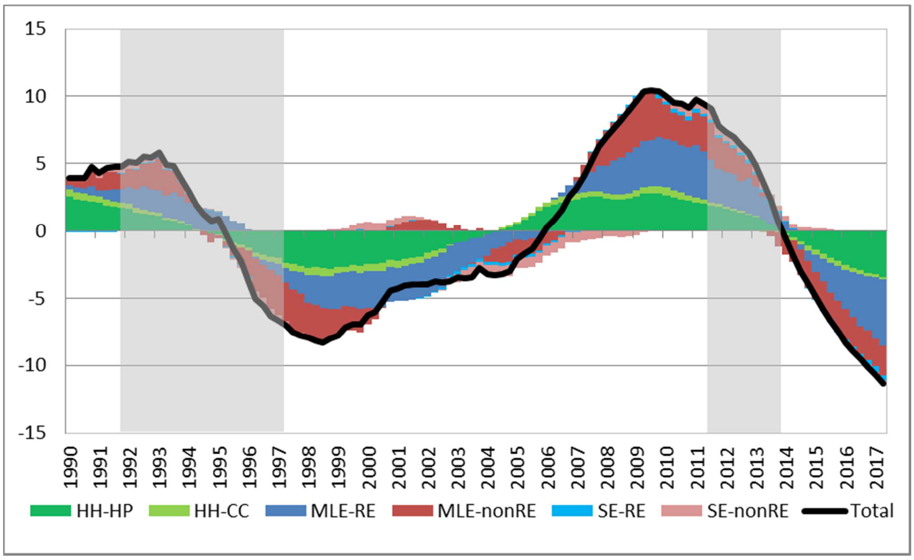
Source: Bank of Italy. The credit-to-GDP gap at sectoral level is the deviation of the actual credit-to-GDP ratio for each sector from its long-term trend, as estimated by applying a two-sided HP filter with a smoothing parameter of 400,000. The credit sectors are non-financial corporations (NFC) and consumer households (HH). Grey shaded areas identify systemic banking crises, as sourced from the ECB/ESRB EU crises database.

Panel B. Four-sector decomposition of the credit-to-GDP gap



Source: Bank of Italy. The credit-to-GDP gap at sectoral level is calculated as the actual credit-to-GDP ratio for each sector minus its long-term trend, which is estimated by applying a two-sided HP filter with a smoothing parameter of 400,000. The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC). Grey shaded areas identify systemic banking crises, as sourced from the ECB/ESRB EU crises database.

Panel C. Six-sector decomposition of the credit-to-GDP gap



Source: Bank of Italy. The credit-to-GDP gap at sectoral level is calculated as the actual credit-to-GDP ratio for each sector minus its long-term trend, which is estimated by applying a two-sided HP filter with a smoothing parameter of 400,000. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC). Grey shaded areas identify systemic banking crises, as sourced from the ECB/ESRB EU crises database.

Assessing whether or not the sectoral cycles are simultaneously above or below their trends is particularly important for the CCyB. The lead/lag relationships for pairwise phase synchronization are shown in Table 3. The entries in the lower triangular part of the table show the pairwise contemporaneous gap synchronization ($\mu_{i,j,0}$), while the entries in the upper triangular part display the lead/lag within a six-year window ($\widehat{h_{i,j}}$) where the degree of synchronization reaches its highest value.[11] A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle.

In a two-sector decomposition (Table 3, Panel A) the contemporaneous phase synchronization between the cycle for the corporate sector (NFC) and the overall cycle is high (0.91) and the aggregate cycle leads the sectoral cycle by one quarter. On the contrary, the credit cycle for consumer households leads the aggregate cycle by three quarters and the contemporaneous phase synchronization between the two is still high though lower (0.82). Pairwise contemporaneous phase synchronization between the sectoral credit cycles and the total cycle decreases as we move from a two-sector to a six-sector decomposition. In the four-sector decomposition (Table 3, Panel B) contemporaneous synchronization with the credit cycle remains high for HH-HP (0.85) and NFC-RE (0.87) while it decreases for HH-CC (0.67) and NFC-nonRE (0.67). Moreover, while the cycles driven by HH-HP, HH-CC and NFC-nonRE have leading properties, the cycle driven by NFC-RE lags the credit cycle by two quarters. In the most granular sectoral decomposition (Table 3, Panel C) phase synchronization decreases further for MLE-nonRE (0.61), SE-RE (0.39) and SE-nonRE (0.30). Some sectoral cycles lead the overall credit cycle (HH-HP, HH-CC and MLE-nonRE) within one year, while others lag: MLE-RE within one year, and SE-RE and SE-nonRE within two years.

Most sectoral gaps are synchronized with the overall cycle within a relatively short period of time, meaning that credit developments in those sectors tend to spread out to other sectors. On the contrary, other cycles, such as those driven by small enterprises, are very poorly synchronized either with the overall cycle or with the other sectoral cycles (e.g. with HH-HP and HH-CC but also with MLE-RE and MLE-nonRE). This result seems consistent with the empirical evidence according to which small enterprises tend to be less exposed to cyclical fluctuations.

The lead/lag relationships for pairwise swing synchronization, which signals whether two cycles are both in upswing or downswing, are shown in Table 4 for each sectoral decomposition (Panel A,B,C). As in Table 3, the entries in the lower triangular part of the table show the pairwise contemporaneous swing synchronization, while the entries in the upper triangular part display the lead/lag within a six-year window where swing synchronization reaches its peak. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. In each panel swing synchronization is weaker than the corresponding gap synchronization. Moreover, it reaches its peak at longer leads for HH-HP and HH-CC and lag for SE-RE (Table 4, Panel C).

[11] Maximum pairwise synchronization values are shown in Appendix 3.

Table 3. Pairwise phase synchronization with lead/lag relationships

(# quarters and per cent)

Panel A. Two-sector decomposition

	NFC	HH	Overall cycle
NFC	1	-4	-1
HH	0.72	1	3
Overall cycle	0.91	0.82	1

Note: The entries in the lower triangular part show the pairwise contemporaneous gap synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are non-financial corporations (NFC) and consumer households (HH).

Panel B. Four-sector decomposition

	NFC-RE	NFC-nonRE	HH-HP	HH-CC	Overall cycle
NFC-RE	1	-3	-5	-6	-2
NFC-nonRE	0.61	1	1	-2	1
HH-HP	0.72	0.60	1	-3	2
HH-CC	0.54	0.49	0.82	1	3
Overall cycle	0.87	0.67	0.85	0.67	1

Note: The entries in the lower triangular part show the pairwise contemporaneous gap synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Panel C. Six-sector decomposition

	HH-HP	HH-CC	MLE-RE	MLE-nonRE	SE-RE	SE-nonRE	Overall cycle
HH-HP	1	-3	6	-1	12	24	2
HH-CC	0.82	1	7	0	14	24	3
MLE-RE	0.72	0.54	1	-4	5	7	-2
MLE-nonRE	0.54	0.58	0.52	1	2	3	2
SE-RE	0.25	0.06	0.38	0.30	1	6	-5
SE-nonRE	0.16	-0.03	0.28	0.32	0.47	1	-9
Overall cycle	0.85	0.67	0.87	0.61	0.39	0.30	1

Note: The entries in the lower triangular part show the pairwise contemporaneous gap synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Table 4. Pairwise swing synchronization with lead/lag relationships

(# quarters and per cent)

Panel A. Two-sector decomposition

	NFC	HH	Overall cycle
NFC	1	-7	0
HH	0.32	1	9
Overall cycle	0.74	0.58	1

Note: The entries in the lower triangular part show the pairwise contemporaneous swing synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are non-financial corporations (NFC) and consumer households (HH).

Panel B. Four-sector decomposition

	NFC-RE	NFC-nonRE	HH-HP	HH-CC	Overall cycle
NFC-RE	1	1	-6	-6	0
NFC-nonRE	0.30	1	-7	-9	0
HH-HP	0.34	0.19	1	-2	9
HH-CC	0.25	0.14	0.61	1	9
Overall cycle	0.60	0.56	0.56	0.39	1

Note: The entries in the lower triangular part show the pairwise contemporaneous swing synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Panel C. Six-sector decomposition

	HH-HP	HH-CC	MLE-RE	MLE-nonRE	SE-RE	SE-nonRE	Overall cycle
HH-HP	1	-2	14	7	13	17	9
HH-CC	0.61	1	10	9	12	18	9
MLE-RE	0.38	0.25	1	-7	0	1	0
MLE-nonRE	0.21	0.16	0.21	1	6	-5	0
SE-RE	0.14	0.05	0.39	0.05	1	1	-7
SE-nonRE	0.12	-0.05	0.12	0.21	0.32	1	0
Overall cycle	0.56	0.39	0.60	0.50	0.32	0.27	1

Note: The entries in the lower triangular part show the pairwise contemporaneous swing synchronization, while the entries in the upper triangular part display the lead/lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads and lags. A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Shifts in sectoral gaps along with weak swing synchronization imply that the level of sectoral disaggregation matters for policymaking as the timing for policy decisions and the appropriate policy response could be different when accounting for the granularity level in the risk assessment framework.

To investigate the causality of the intertemporal relationships across cycles, we run a set of in-sample Granger causality tests based on trivariate regressions, where each sector-specific gap (total gap) is regressed into its own lags, the total gap (each sectoral gap) at different lags and including the business cycle as control variable.[12] The idea is to see whether the total gap monitored by policymakers in real time is able to capture cross-sectoral dynamics without the need to look at sectoral developments. Table 5 tests the null hypotheses that the aggregate credit cycle has no predictive power for a sector-specific gap. Results show that these hypotheses cannot be rejected for almost all sectors except for NFC-nonRE, MLE-nonRE and SE-nonRE at higher lags. This means that the total gap mimics quite well the NFC-nonRE and its main components but this is not the case for the HH-HP and HH-CC sectors as well as for NFC-RE and MLE-RE.

Table 5. Granger Causality Test:
Does the total gap Granger cause a sector-specific gap?
(p value)

Sectoral breakdown	total gap → sectoral gaps	Lag 1	2	3	4	5	6	7	8
2	HH	0.41	0.65	0.78	0.94	0.99	0.99	0.96	0.97
	NFC	0.85	0.21	0.13	**0.06**	**0.06**	**0.09**	0.19	0.29
4	HH-HP	0.39	0.64	0.68	0.87	0.96	0.94	0.92	0.94
	HH-CC	0.59	0.73	0.86	0.85	0.91	0.92	0.92	0.97
	NFC-RE	0.15	0.54	0.96	0.77	0.79	0.83	**0.02**	**0.06**
	NFC-nonRE	**0.02**	**0.01**	**0**	**0.01**	**0.01**	**0**	**0.01**	**0**
6	HH-HP	0.39	0.64	0.68	0.87	0.96	0.94	0.92	0.94
	HH-CC	0.59	0.73	0.86	0.85	0.91	0.92	0.92	0.97
	MLE-RE	0.13	0.72	0.84	0.75	0.77	0.87	**0.10**	0.29
	MLE-nonRE	**0.09**	**0.02**	**0**	**0.01**	**0**	**0**	**0.01**	**0**
	SE-RE	0.87	0.57	0.68	0.51	0.39	0.52	0.23	0.29
	SE-nonRE	0.21	**0.03**	0.2	**0.04**	**0.05**	**0.04**	**0.01**	**0.01**

Note: In the column X->Y, the null hypothesis is that X does not Granger cause Y. Each sector-specific gap is regressed into its own lags, the total gap at different lags and including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); consumer households (HH); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

[12] All the variables in the test have been differenced in order to achieve stationarity, where needed. Results without controlling for the business cycle are shown in Appendix 5. The business cycle is measured as the deviation of real GDP growth from its long-term trend applying a two-sided HP filter with a smoothing parameter of 1,600.

Table 6. Granger Causality Test:

Does a sector-specific gap Granger cause the total gap?

(p value)

Sectoral breakdown	sectoral gaps → total gap	Lag 1	2	3	4	5	6	7	8
2	HH	0.90	0.38	0.13	**0.04**	**0.06**	**0.08**	0.21	0.31
	NFC	0.89	0.37	0.12	**0.05**	**0.05**	**0.07**	0.22	0.30
4	HH-HP	0.98	0.37	0.15	**0.06**	**0.08**	0.12	0.27	0.4
	HH-CC	0.62	0.73	0.59	0.44	0.62	0.68	0.84	0.87
	NFC-RE	**0.07**	0.12	**0.09**	0.16	0.21	0.24	0.19	0.11
	NFC-nonRE	**0.05**	**0.05**	**0.06**	**0.05**	**0.09**	**0.08**	**0.09**	**0.09**
6	HH-HP	0.98	0.37	0.15	**0.06**	**0.08**	0.12	0.27	0.4
	HH-CC	0.62	0.73	0.59	0.44	0.62	0.68	0.84	0.87
	MLE-RE	0.12	0.25	0.20	0.29	0.39	0.51	0.43	0.25
	MLE-nonRE	0.12	0.12	0.19	0.23	0.17	0.13	0.16	0.24
	SE-RE	**0.10**	0.21	0.23	0.47	0.23	0.16	0.25	0.41
	SE-nonRE	0.22	0.52	0.51	0.28	0.50	0.58	0.51	**0.03**

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. Total gap is regressed into its own lags, each sectoral gap at different lags and including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); consumer households (HH); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Conversely, Table 6 reports the outcome of the tests under the null hypothesis that a sector-specific cycle has no predictive power for the aggregate cycle. The sectoral gaps do not Granger cause the credit cycle when the test is run on higher degrees of sector granularity. Results are confirmed overall when the marginal predictive value of the total gap (sectoral gaps) for the sectoral gaps (total gap) is tested without controlling for the business cycle.[13]

7. Contribution of sectoral imbalances to systemic stress

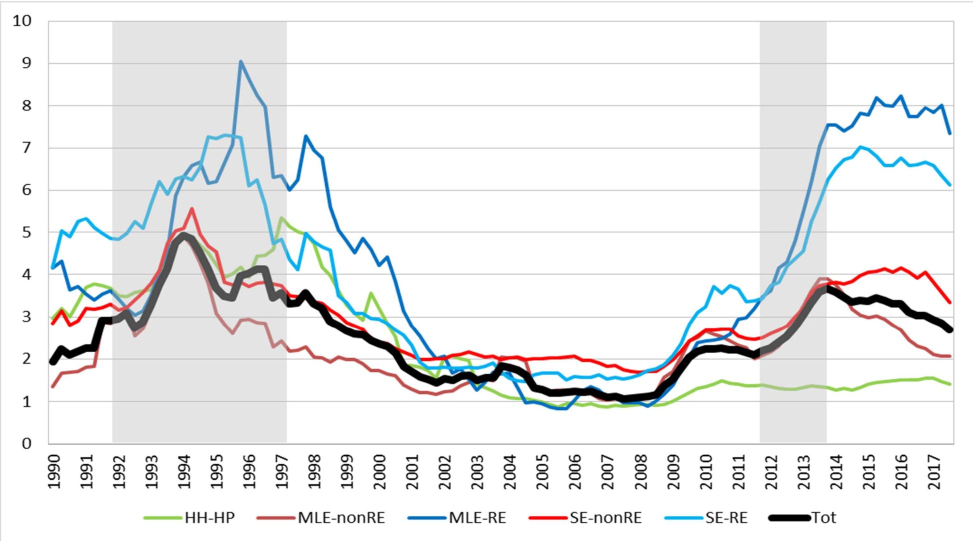
As macroprudential policy takes a system-wide perspective, the attention of policymakers should be devoted to sectors that may entail risks for the broader financial system. The systemic relevance of a credit segment can be driven either by its size relative to the financial system (e.g. in terms of gross exposure or risk exposure amount) or by its contribution to cyclical systemic stress. We have already discussed sector size in Section 4. We now focus on the dimension of credit risk. As a measure of cyclical systemic stress we use the aggregate new bad debt rate, given by the flow of new bad loans over the year as a percentage of the average stock of outstanding loans in the same year. Bad loans represent the worst status of non-performing loans. They are exposures to insolvent debtors or debtors in similar circumstances. A rise in the system-wide level of new bad loans

[13] See Tables A5.1 and A5.2 in Appendix 5.

relative to total loans signals a surge in systemic credit risk. To assess the riskiness of each credit segment and its contribution to cyclical systemic risk we also analyse the evolution of new bad debt rates at sectoral level. Figure 4 shows the dynamics of new bad debt rates over time: the aggregate rate in Italy (black line) reached a peak in the mid-1990s and in the aftermath of the global financial crisis, in conjunction with the two main systemic banking crises; over the sample period new bad debt rates in the real estate sectors were much higher and more volatile than those observed in other sectors (blue lines); the same also holds controlling for firm size; new bad debt rates for residential mortgages followed a different pattern and become smoother in recent years.[14]

Figure 4. Systemic and sectoral credit risk

(per cent)



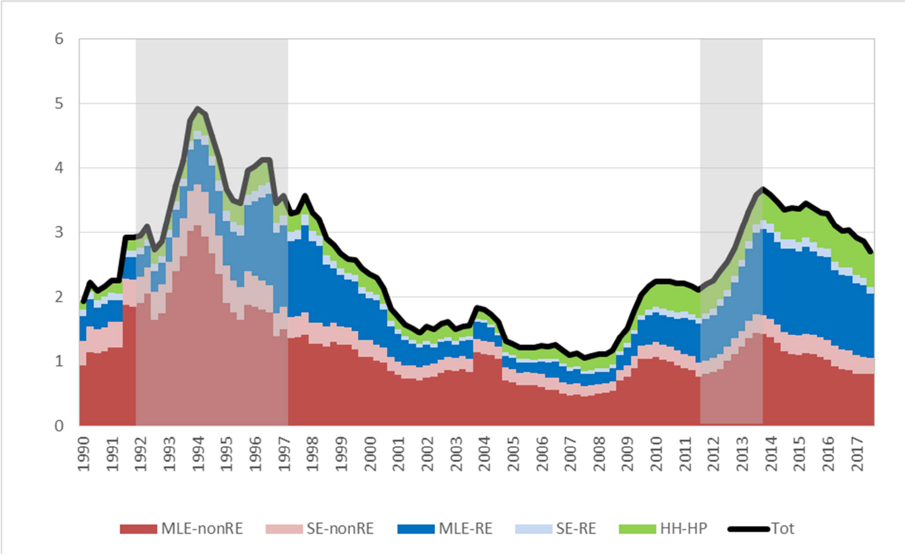
Source: Bank of Italy, Central Credit Register. Bad debts are exposures to debtors that are insolvent or in substantially similar circumstances. New bad debt rates are annualized by dividing the sum of quarterly flows of new bad debts over the year to the average stock of outstanding loans in the corresponding year. Data are seasonally adjusted where necessary. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); and mortgage loans (HH-HP). Grey shaded areas identify systemic banking crises, as sourced from the ECB/ESRB EU crises database.

Graphic inspection also shows that the contribution of each sector to systemic stress differs quite significantly (Figure 5). The contribution to the aggregate default rate was much higher for the credit segment relating to medium and large non-financial corporations and much lower for mortgage lending. Since the last peak in 2014, the contributions of both MLE-nonRE and MLE-RE have levelled off.

[14] Data on bad debt rates for consumer loans are not available.

Figure 5. Sectoral risk contribution to systemic stress

(per cent)



Source: Bank of Italy, Central Credit Register. Bad debts are exposures to debtors that are insolvent or in substantially similar circumstances. New bad debt rates are annualized by dividing the sum of quarterly flows of new bad debts over the year to the average stock of outstanding loans in the corresponding year. Data are seasonally adjusted where necessary. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); and mortgage loans (HH-HP). Grey shaded areas identify systemic banking crises, as sourced from the ECB/ESRB EU crises database.

As in Section 6, we run a set of in-sample Granger causality tests to investigate the causality of the relationships between the imbalances at sectoral level and the aggregate default rate. The system-wide new bad debt rate is regressed into its own lags, each sectoral gap at different lags and including the business cycle as control variable. Table 7 reports the outcomes of the tests at different lags under the null hypothesis that a sector-specific credit cycle has no predictive power for the aggregate default rate. Granger causality tests show that the sectoral imbalances driven by medium and large non-financial corporations in the non-real-estate-related segments Granger cause systemic stress, as proxied by the aggregate default rate. Conversely, imbalances in the real-estate-related corporate sector give rise to a surge in credit risk which does not spill over into other sectors. For mortgage lending (HH-HP), results are mixed. Contagion seems to come into play with a four-quarter lag, but the result is not confirmed when we run the same test without controlling for the output gap.[15]

These results are broadly consistent with those in Accornero et al. (2017), who leverage on micro data.

[15] See Table A5.3 in Appendix 5.

Table 7. Granger Causality Test

Does a sector-specific gap Granger cause systemic stress?

(p value)

Sectoral breakdown	sectoral cycle → aggregate credit risk	Lag							
		1	2	3	4	5	6	7	8
2	HH	0.81	0.40	0.18	**0.04**	**0.06**	**0.08**	**0.04**	**0.04**
	NFC	0.58	**0**	**0**	**0.01**	**0.04**	0.14	0.27	0.12
4	HH-HP	0.99	0.60	0.39	**0.05**	**0.05**	**0.06**	**0.09**	**0.09**
	NFC-RE	0.67	**0.10**	0.24	0.41	0.78	0.94	0.92	0.52
	NFC-nonRE	0.34	**0.04**	**0.01**	**0.04**	**0.06**	0.21	0.39	0.25
6	HH-HP	0.99	0.60	0.39	**0.05**	**0.05**	**0.06**	**0.09**	**0.09**
	MLE-RE	0.78	0.15	0.31	0.52	0.84	0.97	0.92	0.63
	MLE-nonRE	0.34	**0.02**	**0.01**	**0.03**	**0.06**	0.22	0.3	0.18
	SE-RE	0.43	0.46	0.71	0.64	0.53	0.41	0.75	0.80
	SE-nonRE	0.88	0.46	0.46	0.65	0.52	0.46	0.58	0.79

Note: In the column X->Y, the null hypothesis is that X does not Granger cause Y. The system-wide new bad debt rate is regressed into its own lags, each sectoral gap at different lags and including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); consumer households (HH); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); and mortgage loans (HH-HP).

8. Implications for CCyB decisions

As a final step we illustrate how our analyses of sectoral cycles can affect policy decisions on CCyB. Assuming that both the broad-based CCyB and the sectoral CCyB were already in place before the global financial crisis, we try to deduce what policy action could have been taken to strengthen banking sector resilience ahead of the crisis.

To this end we map the sectoral credit cycles into sectoral buffer rates applying the threshold values proposed by Basel III. According to BCBS (2010), the buffer rate is nil until the credit-to-GDP gap is below 2 per cent and takes the value 2.5 when the gap is above 10 per cent; for values of the gap between these two thresholds the buffer rate increases linearly with the gap:

$$BR_{i,t} = \begin{cases} 0 & \text{if } \widetilde{c_{i,t}} < 2 \\ (\widetilde{c_{i,t}} - 2) \cdot \dfrac{5}{16} & \text{if } 2 \leq \widetilde{c_{i,t}} < 10 \\ 2.5 & \text{if } \widetilde{c_{i,t}} \geq 10 \end{cases}$$

In order to make those threshold values also relevant for the credit-to-GDP gaps at sectoral level, we normalize the sectoral gaps by a scaling factor given by the ratio between the standard deviation of the aggregate cycle and that of each sectoral credit cycle, as follows:

$$\widetilde{c_{i,t}} = c_{i,t} \cdot \frac{std(c_{Tot})}{std(c_i)} \quad \text{s. t.} \qquad \mathrm{std}(\widetilde{c_i}) = \mathrm{std}(c_{Tot})$$

where $c_{i,t}$ is the credit cycle of sector i at time t as measured by the credit-to-GDP gap, $\widetilde{c_{i,t}}$ is the normalized gap, and c_{Tot} is the aggregate credit gap. The rescaling was needed because the levels of the sectoral gaps and their amplitude differ quite significantly compared with the aggregate credit gap.[16]

Once the sectoral cycles have been translated into buffer rates, we compare the evolution of the latter with the broad-based buffer rate over the period 1990-2017 (Figure 6). Green cells identifies 'normal times', when the buffer rates are supposed to be nil, while red cells indicate either 'boom times' (light red), when the buffer rates should increase linearly with the gaps, or 'bad times' (dark red), when risk is likely to materialize and the buffer rate must be available for release.
The credit gap for consumer lending moved first into positive territory in 2003, followed by mortgage lending one year later (in 2004). The increase in lending to households did not have any impact on the total gap, which remained negative until 2006. The sectoral developments in consumer and household lending would have required close monitoring by policymakers in order to inform decisions on sectoral CCyBs. The monitoring of credit developments could have been complemented with analyses of micro data to assess whether credit developments were associated with a concentration of cyclical systemic risks in vulnerable households. Given that the growth in credit to households was not associated with imbalances in more vulnerable households, we can reasonably argue that there was no need to build up a sectoral buffer to increase banks' resilience in these targeted segments. Ex post, we learnt that credit risk for households remained limited overall and well below the level of risk observed in the '90s recession, even in the absence of policy intervention.

The total gap began to move into positive territory in 2006, along with the MLE-RE sector. The MLE-nonRE gap became positive one year later (in 2007) but peaked at a faster pace, one year before the total gap (the former peaked in 2008 and the latter in 2009). The SE-RE gap immediately followed, although at a slower pace, while the SE-nonRE gap moved last (2009). In relative terms, the bulk of the credit boom was concentrated in the MLE-nonRE, MLE-RE and SE-RE sectors and it was associated with a steady increase in sectoral default rates that began in 2008 and was amplified by two severe economic recessions.[17] A credit boom in these sectors would have required close monitoring by risk analysts to detect a possible concentration of imbalances in vulnerable firms. Ex post, we observed that most of the contribution to the system-wide new bad debt rate

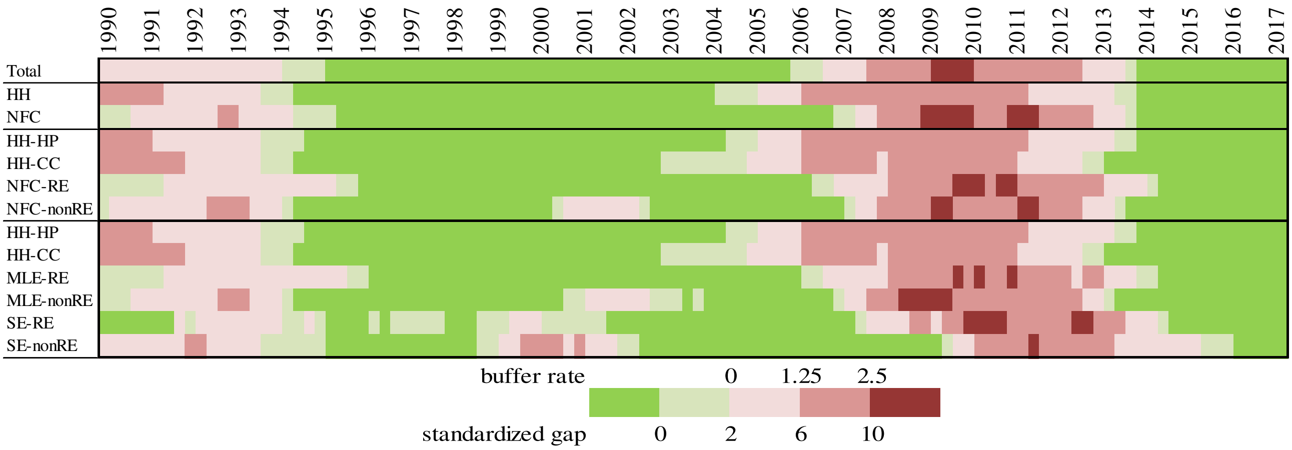
[16] See Table A1.1 in Appendix 1. This is partly due to the fact that the sectoral cycles are all obtained as gaps of the sectoral credit divided by GDP, which tends to be very large compared with some of the credit segments (e.g. SE-RE).

[17] The former occurred in 2008-09 when Italian GDP contracted by 6.5 per cent, while the latter occurred in 2012-13 when Italian GDP contracted by 4.5 per cent.

came from MLE-nonRE and MLE-RE, while the contribution of SE-RE to systemic stress was not as important.

Figure 6. Sectoral buffer rates

(per cent)



Note: The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); mortgage loans (HH-HP); and other consumer loans (HH-CC). Green cells identifies 'normal times', when the standardized gap is below 2 per cent and the buffer rate is nil, while red cells indicate either 'boom times' (light red), when the buffer rates should increase linearly with the gaps, or 'bad times' (dark red), when risk is likely to materialize and the buffer rate must be available for release.

From a policy perspective we can argue that the monitoring of sectoral developments would have impacted not just the timing for activation of the broad-based CCyB, but rather the size of the buffer, as the sectoral buffer for MLE-nonRE reached its peak one year before the broad-based buffer. Activation of the broad-based buffer could reasonably have been announced in 2006 to become effective in 2007. The buffer rate could have been set at 1.5 per cent first and eventually tightened to reflect developments in MLE-nonRE. Since almost all sectoral gaps were in red territory, the activation of a broad-based CCyB would have helped to build up resilience against potential cyclical risks from those sectors as well, except SE-nonRE, whose gap remained negative until 2009. This sector would have been unduly penalized by a broad-based CCyB as banks might have had an incentive to move away from loans with higher risk weights.

There is another reason why, at that time, the decision between a broad-based CCyB and a sectoral CCyB (for the MLE-nonRE sector) would not have been so straightforward. From Granger causality analyses we learn that sectoral imbalances driven by the MLE-nonRE segment cause systemic stress. In circumstances where credit exuberance in a sector is combined with expectations of more widespread losses, the choice between a sectoral CCyB and a broad-based one is not clear-cut. If potential loss spill-overs to untargeted segments are not adequately taken into account in calibrating the targeted tool, then there might be a risk of building up insufficient capital buffers. Moreover, it is worth remembering that in the case of a sectoral CCyB the additional capital requirement is imposed on sectoral RWA. As a result, for the same level of the buffer rate, the amount of capital raised with a sectoral tool is much less. This is an additional aspect that needs to be taken into consideration in calibrating a targeted buffer.

As for the real-estate-related corporate segment, in Italy imbalances here give rise to a surge in sectoral default rates that does not spill over into other sectors. In this case, should the imbalances be confined to the MLE-RE and SE-RE sectors, a sectoral CCyB could help to correct them without raising the cost of credit in other sectors.

A better understanding of the trade-offs associated with the choice between a sectoral tool and a broad-based one, as well as the complementary aspects relating to their joint use, is left to future research.

9. Conclusions

We study the cyclical properties of different credit segments to check whether there is sufficient empirical support in Italy for the introduction of a sectoral CCyB in the macroprudential framework. We found that the degree of pairwise phase as well as swing synchronization decreases as we move from a two-sector to a six-sector decomposition of the credit-to-GDP gap. As for the relationships between sector-specific credit cycles and the aggregate cycle, we find that business lending plays a major role in driving the credit cycle in Italy. Exuberance in the NFC-nonRE sector leads to broad-based credit exuberance within a short period of time and is usually followed by a surge in the system-wide new bad debt rate. By contrast, the increase in new bad debt rates following exuberance in the commercial real estate segment does not spill over into other sectors. Taken together these results suggest a sectoral CCyB could be a useful addition to the macroprudential framework as both the timing for activation and the size of a broad-based CCyB rate could be different when accounting for the sectoral dimension of the credit-to-GDP gap.

From a policy perspective, we conclude that sectoral credit segments warrant careful monitoring because their systemic relevance, prudential requirements and exposure to cyclical systemic risks differ quite substantially. Booms in real-estate sector-specific exposures in Italy could be addressed more effectively with targeted tools, as the CCyB would unduly penalize other types of business lending. However, where credit exuberance in a sector is combined with expectations of more widespread losses, the choice between a sectoral CCyB and a broad-based one might not be clear-cut. A policy framework in which both broad-based credit and sectoral credit imbalances are strictly monitored, along with their implications for financial stability, would provide policymakers with sufficient information to select the most appropriate tool. In the presence of data constraints, the six-sector decomposition could strike the right balance between the required sectoral granularity and relevance for policymaking, to the extent that it controls for sector of activity and firm size, exposure to cyclical fluctuations and prudential capital requirements.

These findings cannot be easily generalized to other countries as the choices made regarding the definition of the credit segments, the filtering technique to extract the cycles, and the use of the new bad debt rate to measure cyclical systemic risk reflect country specificities in Italy. Moreover, some of the findings might depend on the sectoral granularity applied in the analyses, which in turn reflects data availability in Italy.

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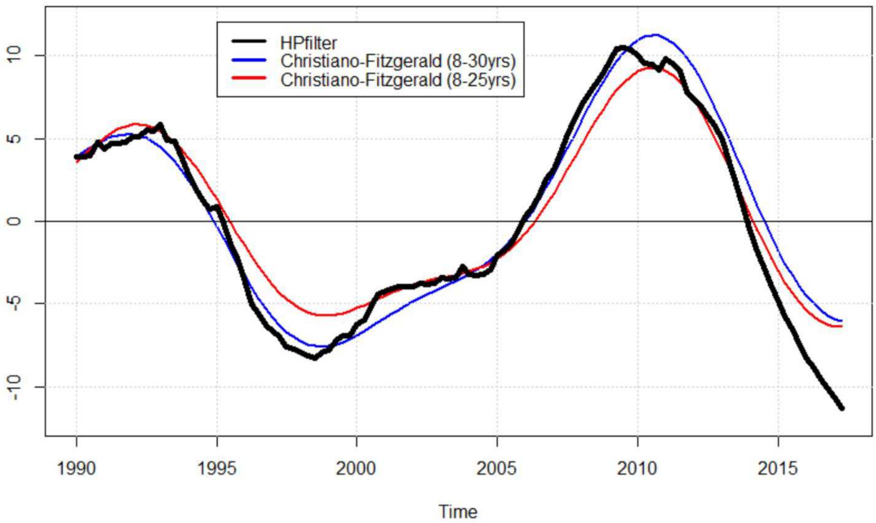
Appendix

Appendix 1. Total and sectoral credit cycles

Figure A1.1. Different measures of the Italian financial cycle
(per cent)



Note: The HP filter is a two-sided filter with a smoothing parameter of 400,000, consistently with Alessandri et al. (2015). The band pass filter à la Christiano and Fitzgerald extracts the cycle by isolating the medium-to-long-term frequencies, i. e. between 8 and 25 or between 8 and 30 years.

Table A1.1. Descriptive statistics of credit cycles
(per cent)

Sectoral breakdown	Sector	Mean	Median	Standard deviation	Min	Max
	Total	0.0	-0.6	6.0	-11.3	10.5
2	HH	0.0	0.1	2.3	-3.6	3.3
	NFC	0.0	-1.0	4.0	-7.7	7.3
4	HH-HP	0.0	0.1	1.9	-3.4	2.8
	HH-CC	0.0	0.0	0.4	-0.6	0.6
	NFC-RE	0.0	0.2	2.3	-5.4	4.1
	NFC-nonRE	0.0	-0.3	2.0	-3.4	3.6
6	HH-HP	0.0	0.1	1.9	-3.4	2.8
	HH-CC	0.0	0.0	0.4	-0.6	0.6
	MLE-RE	0.0	0.2	2.2	-4.9	3.8
	MLE-nonRE	0.0	0.1	1.8	-3.1	3.7
	SE-RE	0.0	0.0	0.2	-0.4	0.3
	SE-nonRE	0.0	0.1	0.5	-0.8	0.8

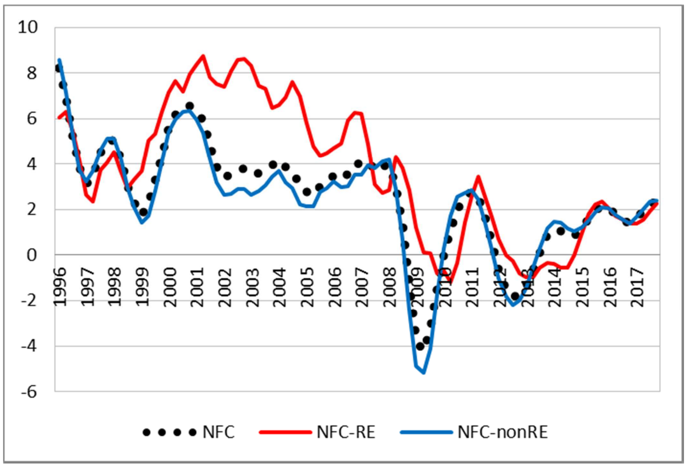
Note: The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Appendix 2. Robustness checks using sectoral value added instead of GDP

A regulatory framework for a sectoral CCyB is still missing and the existing one is not explicit about what denominator to consider when computing the sectoral credit-to-GDP ratios. It is not straightforward that the GDP is the appropriate aggregate to use when targeting a specific sector of exposures. For instance, for the corporate sector it could be argued that the sectoral business cycles are better represented by the corresponding value added. The idea is that, in order to assess the build-up of sectoral imbalances, credit growth in a specific sector must be compared with the growth of the corresponding value added, which is not necessarily synchronized with the GDP of the entire economy. Figure A2.1 shows that this is the case for the NFC-RE sector, as the business cycle is mainly driven by the NFC-nonRE sector.

Figure A2.1. Value added by NFC sector

(moving average of year-on-year growth rates over three quarters; per cent)



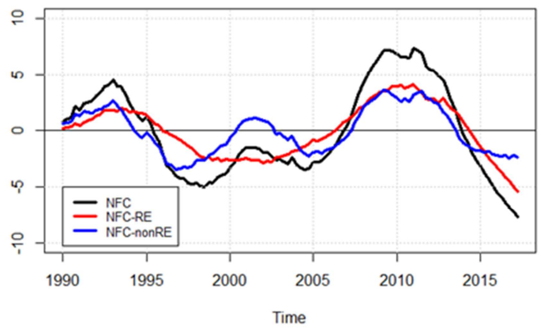
Note: The credit sectors are non-financial corporations (NFC), real-estate-related non-financial corporations (NFC-RE) and non-real-estate-related non-financial corporations (NFC-nonRE).

Therefore, for the corporate sector we replicate the analysis of cyclical properties of the two-sector and four-sector decomposition of the credit cycle in paragraph 6 using the value added in each sector as the denominator of the credit-to-GDP ratios (Figure A2.2).

Results in terms of synchronicity are consistent overall with the ones obtained using GDP as the denominator of the sectoral ratios (Table A2.1).

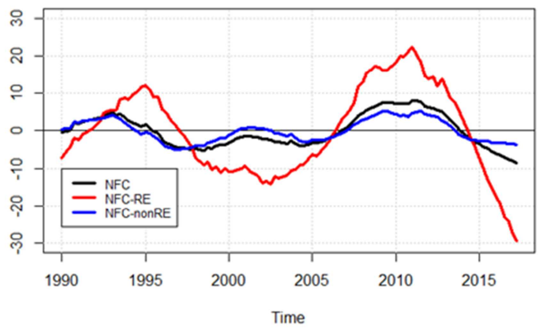
Figure A2.2. NFC sectoral credit gaps

Panel A. Credit-to-GDP gaps



Note: The credit sectors are non-financial corporations (NFC), real-estate-related non-financial corporations (NFC-RE) and non-real-estate-related non-financial corporations (NFC-nonRE).

Panel B. Credit-to-value-added gaps



Note: The credit sectors are non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE) and non-real-estate-related non-financial corporations (NFC-nonRE).

Table A2.1. Synchronization between the two subsectors of NFC

Panel A. Gap phase synchronization

	NFC-RE	NFC-nonRE	NFC
NFC-RE	1	-3	-2
NFC-nonRE	0.51	1	1
NFC	0.79	0.72	1

Note: The entries in the lower triangular part show the pairwise contemporaneous gap synchronization. The entries in the upper triangular part display the lead or lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads/lags. The credit sectors are non-financial corporations (NFC), real-estate-related non-financial corporations (NFC-RE) and non-real-estate-related non-financial corporations (NFC-nonRE).

Panel B. Swing synchronization

	NFC-RE	NFC-nonRE	NFC
NFC-RE	1	1	0
NFC-nonRE	0.39	1	0
NFC	0.52	0.74	1

Note: The entries in the lower triangular part show the pairwise contemporaneous swing synchronization. The entries in the upper triangular part display the lead or lag (in quarters) corresponding to the maximum cross-synchronization in absolute value when allowing for at most 6 years (24 quarters) of leads/lags. The credit sectors are non-financial corporations (NFC), real-estate-related non-financial corporations (NFC-RE) and non-real-estate-related non-financial corporations (NFC-nonRE).

Appendix 3. Maximum pairwise synchronization

Table A3.1. Pairwise phase synchronization with lead/lag relationships

(# quarters and per cent)

Panel A. Two-sector decomposition

	NFC	HH	Overall cycle
NFC	-	-4	-1
HH	0.8	-	3
Overall cycle	0.9	0.9	-

Note: The entries in the lower triangular part of the table show the highest degree of gap synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters). A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are non-financial corporations (NFC) and consumer households (HH).

Panel B. Four-sector decomposition

	NFC-RE	NFC-nonRE	HH-HP	HH-CC	Overall cycle
NFC-RE	-	-3	-5	24	-2
NFC-nonRE	0.7	-	1	24	1
HH-HP	0.9	0.6	-	-3	2
HH-CC	-0.8	-0.6	0.9	-	3
Overall cycle	0.9	0.7	0.9	0.8	-

Note: The entries in the lower triangular part of the table show the highest degree of gap synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters). A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Panel C. Six-sector decomposition

	HH-HP	HH-CC	MLE-RE	MLE-nonRE	SE-RE	SE-nonRE	Overall cycle
HH-HP	-	-3	6	-1	-12	-18	2
HH-CC	0.9	-	7	0	-11	24	3
MLE-RE	0.9	0.8	-	-4	-18	-20	-2
MLE-nonRE	0.6	0.6	0.6	-	-21	-18	2
SE-RE	-0.5	-0.5	-0.6	-0.6	-	6	17
SE-nonRE	-0.5	0.4	-0.5	-0.8	0.6	-	18
Overall cycle	0.9	0.8	0.9	0.6	-0.6	-0.6	-

Note: The entries in the lower triangular part of the table show the highest degree of gap synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters).A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Table A3.2. Pairwise swing synchronization with lead/lag relationships

(# quarters and per cent)

Panel A. Two-sector decomposition

	NFC	HH	Overall cycle
NFC	-	-7	0
HH	0.5	-	9
Overall cycle	0.7	0.6	-

Note: The entries in the lower triangular part of the table show the highest degree of swing synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters). A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are non-financial corporations (NFC) and consumer households (HH).

Panel B. Four-sector decomposition

	NFC-RE	NFC-nonRE	HH-HP	HH-CC	Overall cycle
NFC-RE	-	1	-6	-6	0
NFC-nonRE	0.4	-	-7	-9	0
HH-HP	0.6	0.3	-	-2	9
HH-CC	0.5	0.4	0.6	-	9
Overall cycle	0.6	0.6	0.6	0.5	-

Note: The entries in the lower triangular part of the table show the highest degree of swing synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters). A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

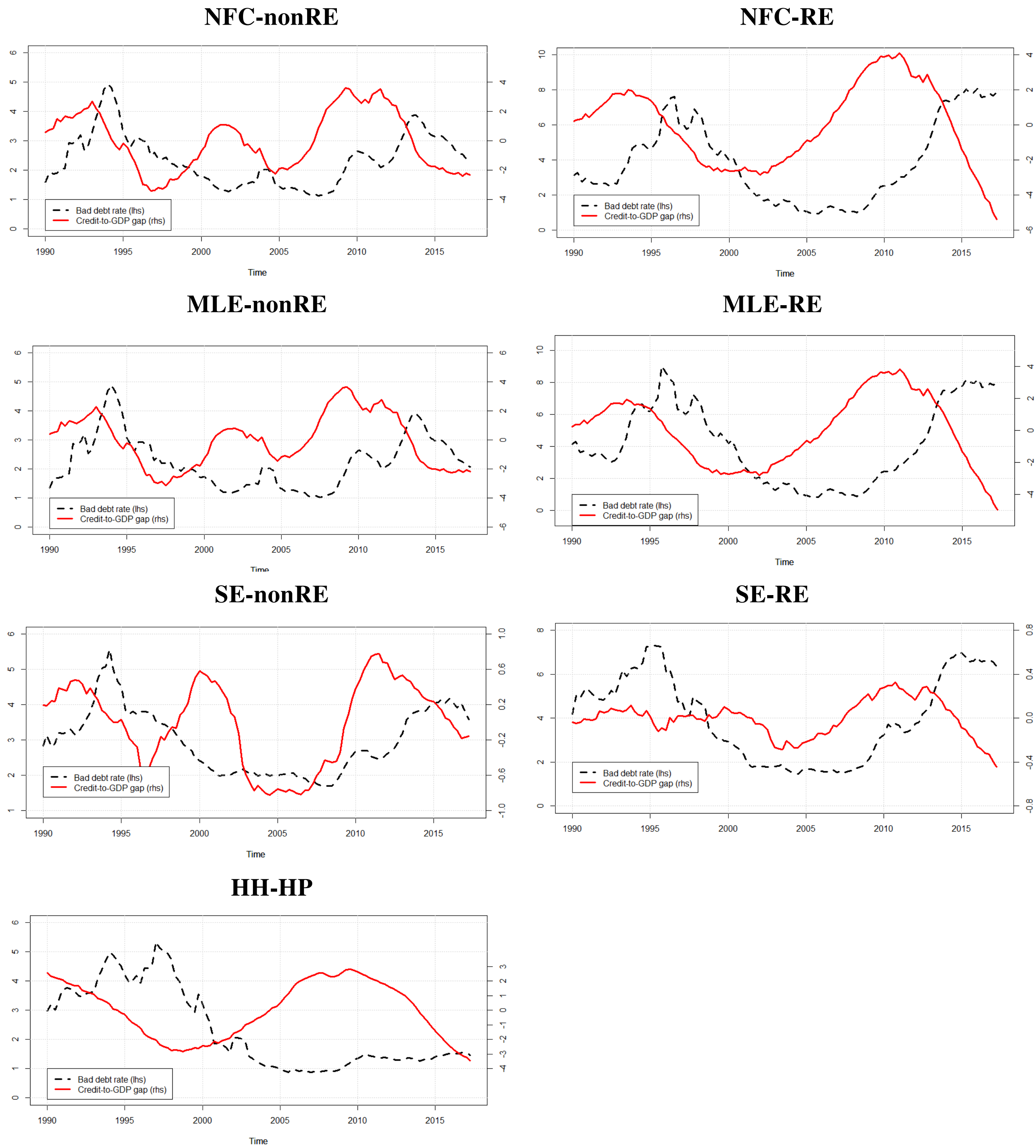
Panel C. Six-sector decomposition

	HH-HP	HH-CC	MLE-RE	MLE-nonRE	SE-RE	SE-nonRE	Overall cycle
HH-HP	-	-2	14	7	13	17	9
HH-CC	0.6	-	10	9	12	18	9
MLE-RE	0.6	0.5	-	-7	0	1	0
MLE-nonRE	0.3	0.3	0.4	-	-20	-21	0
SE-RE	0.5	0.4	0.4	-0.3	-	1	19
SE-nonRE	0.3	0.4	0.2	-0.4	0.4	-	20
Overall cycle	0.6	0.5	0.6	0.5	-0.4	-0.4	-

Note: The entries in the lower triangular part of the table show the highest degree of swing synchronization (in absolute value) within the six-year window, while the entries in the upper triangular part display the optimal leads/lags in quarters when allowing for at most six years (24 quarters). A positive entry indicates that the row cycle leads the column cycle, while a negative entry indicates that the row cycle lags the column cycle. The credit sectors are: real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Appendix 4. Contribution of sectoral credit exuberance to sectoral stress

Figure A4.1. Sectoral credit-to-GDP gap and sectoral bad debt rate



Note: The credit sectors are: real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); and mortgage loans (HH-HP).

Appendix 5. Granger causality tests without controlling for the business cycle

Table A5.1. Granger Causality Test:

Does the total gap Granger cause a sector-specific gap?

(p value)

Sectoral breakdown	total gap → sectoral gap	Lag 1	2	3	4	5	6	7	8
2	HH	0.41	0.69	0.77	0.96	0.99	0.98	0.96	0.89
	NFC	0.88	0.41	0.13	0.11	**0.06**	**0.09**	0.15	0.2
4	HH-HP	0.39	0.65	0.68	0.92	0.97	0.93	0.92	0.89
	HH-CC	0.57	0.74	0.79	0.84	0.87	0.9	0.89	0.96
	NFC-RE	0.16	0.53	0.91	0.85	0.88	0.88	**0.03**	**0.02**
	NFC-nonRE	**0.02**	**0.03**	**0.03**	**0.04**	**0.06**	**0.06**	0.11	**0.03**
6	HH-HP	0.39	0.65	0.68	0.92	0.97	0.93	0.92	0.89
	HH-CC	0.57	0.74	0.79	0.84	0.87	0.9	0.89	0.96
	MLE-RE	0.13	0.72	0.89	0.87	0.89	0.93	0.12	0.14
	MLE-nonRE	**0.10**	0.23	0.21	0.17	0.18	**0.05**	0.14	**0.07**
	SE-RE	0.88	0.56	0.69	0.65	0.65	0.77	0.36	0.44
	SE-nonRE	0.20	**0.10**	0.26	**0.07**	**0.06**	**0.05**	**0.03**	**0.01**

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. A sector-specific gap is regressed into its own lags, the total gap at different lags without including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Table A5.2. Granger Causality Test:

Does a sector-specific gap Granger cause the total gap?

(p value)

Sectoral breakdown	sectoral gap → total gap	Lag 1	2	3	4	5	6	7	8
2	HH	0.9	0.57	0.13	**0.1**	**0.09**	0.12	0.22	0.31
	NFC	0.89	0.57	0.13	**0.1**	**0.09**	0.12	0.22	0.31
4	HH-HP	0.99	0.52	0.16	0.13	0.12	0.15	0.27	0.36
	HH-CC	0.61	0.86	0.58	0.56	0.71	0.82	0.92	0.96
	NFC-RE	**0.06**	0.16	0.21	0.36	0.44	0.45	0.37	**0.09**
	NFC-nonRE	**0.05**	0.11	0.14	0.16	0.28	0.38	0.33	0.23
6	HH-HP	0.99	0.52	0.16	0.13	0.12	0.15	0.27	0.36
	HH-CC	0.61	0.86	0.58	0.56	0.71	0.82	0.92	0.96
	MLE-RE	0.12	0.29	0.36	0.53	0.64	0.73	0.69	0.21
	MLE-nonRE	0.12	0.34	0.45	0.61	0.65	0.67	0.56	0.63
	SE-RE	**0.10**	0.26	0.32	0.55	0.39	0.33	0.36	0.49
	SE-nonRE	0.22	0.3	0.29	0.12	0.31	0.44	0.45	**0.02**

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. Total gap is regressed into its own lags, each sectoral gap at different lags without including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); mortgage loans (HH-HP); and other consumer loans (HH-CC).

Table A5.3. Granger Causality Test

Does a sector-specific gap Granger cause systemic stress?

(p value)

Sectoral breakdown	**sectoral cycle → aggregate credit risk**	**Lag**							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
2	HH	0.85	0.91	0.94	0.9	0.49	0.39	0.26	0.14
	NFC	0.56	**0**	**0.01**	**0.04**	**0.08**	0.23	0.31	0.21
4	HH-HP	0.96	0.93	0.92	0.8	0.41	0.25	0.31	0.21
	NFC-RE	0.66	0.18	0.33	0.56	0.86	0.94	0.89	0.66
	NFC-nonRE	0.33	**0.02**	**0.02**	0.13	0.14	0.27	0.28	0.29
6	HH-HP	0.96	0.93	0.92	0.8	0.41	0.25	0.31	0.21
	MLE-RE	0.77	0.24	0.42	0.67	0.87	0.96	0.89	0.77
	MLE-nonRE	0.33	**0.01**	**0.01**	**0.07**	0.12	0.29	0.24	0.21
	SE-RE	0.42	0.48	0.65	0.66	0.64	0.38	0.59	0.58
	SE-nonRE	0.86	0.44	0.52	0.39	0.3	0.26	0.26	0.59

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. The system-wide new bad debt rate is regressed into its own lags, each sectoral gap at different lags without including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); and mortgage loans (HH-HP).

Appendix 6. Contribution of broad-based credit exuberance to sectoral stress

Table A6.1. Granger Causality Test

Does the total credit gap Granger cause the default rate in a specific sector?

(p value)

Panel A. Including the business cycle as control variable

Sectoral breakdown	total gap → sectoral credit risk	Lag 1	2	3	4	5	6	7	8
2	HH	**0.04**	**0.08**	**0.08**	0.14	0.31	0.38	**0.08**	**0.07**
	NFC	0.65	**0**	**0**	**0.01**	**0.06**	0.14	0.16	**0.02**
4	HH-HP	**0.04**	**0.08**	**0.08**	0.14	0.31	0.38	**0.08**	**0.07**
	NFC-RE	**0.09**	**0.07**	**0.09**	0.21	**0.04**	**0.02**	**0.04**	**0.01**
	NFC-nonRE	0.80	**0**	**0**	**0.01**	**0.10**	0.32	0.31	0.14
6	HH-HP	**0.04**	**0.08**	**0.08**	0.14	0.31	0.38	**0.08**	**0.07**
	MLE-RE	0.24	**0.06**	**0.05**	0.25	**0.09**	**0.03**	**0.07**	**0.07**
	MLE-nonRE	0.64	**0**	**0**	**0.01**	0.20	0.40	0.35	0.16
	SE-RE	0.15	0.34	0.77	0.17	0.19	0.28	0.48	0.27
	SE-nonRE	**0.03**	**0.02**	**0.01**	0.25	0.19	0.22	0.39	**0.05**

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. Each sectoral new bad debt rate is regressed into its own lags, total gap at different lags and including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); and mortgage loans (HH-HP).

Panel B. Without including the business cycle as control variable

Sectoral breakdown	total gap → sectoral credit risk	Lag 1	2	3	4	5	6	7	8
2	HH	**0.04**	**0.07**	**0.10**	0.15	0.30	0.42	0.11	0.11
	NFC	0.64	**0.01**	**0**	**0.04**	0.14	0.33	0.39	**0.09**
4	HH-HP	**0.04**	**0.07**	**0.10**	0.15	0.30	0.42	0.11	0.11
	NFC-RE	**0.09**	**0.06**	0.14	0.28	**0.05**	**0.02**	**0.04**	**0.01**
	NFC-nonRE	0.80	**0.01**	**0**	**0.02**	0.18	0.58	0.60	0.36
6	HH-HP	**0.04**	**0.07**	**0.10**	0.15	0.3	0.42	0.11	0.11
	MLE-RE	0.24	**0.05**	0.07	0.36	0.13	**0.02**	**0.05**	**0.04**
	MLE-nonRE	0.64	**0.01**	**0.01**	**0.02**	0.29	0.67	0.69	0.41
	SE-RE	0.15	0.30	0.72	**0.09**	0.15	0.23	0.39	**0.1**
	SE-nonRE	**0.03**	**0.03**	**0.02**	0.35	0.3	0.24	0.33	**0.06**

Note: In column X->Y, the null hypothesis is that X does not Granger cause Y. Each sectoral new bad debt rate is regressed into its own lags, total gap at different lags without including the business cycle as control variable. The credit sectors are: non-financial corporations (NFC); real-estate-related non-financial corporations (NFC-RE); non-real-estate-related non-financial corporations (NFC-nonRE); real-estate-related medium and large enterprises (MLE-RE); non-real-estate-related medium and large enterprises (MLE-nonRE); real-estate-related small enterprises (SE-RE); non-real-estate-related small enterprises (SE-nonRE); consumer households (HH); and mortgage loans (HH-HP).