WHEN CREDIT GROWTH DIVERGES: COMMON DYNAMICS AND REGIONAL HETEROGENEITY IN ITALY

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CLAUDIO BARBIERI
MATTIA GUERINI
MAURO NAPOLETANO

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When Credit Growth Diverges:
Common Dynamics and Regional Heterogeneity in Italy

Claudio Barbieri[a] Mattia Guerini[b,c] Mauro Napoletano[d,f,e]

[a] *European Central Bank*
[b] *Università di Brescia*
[c] *Fondazione ENI Enrico Mattei*
[d] *Université Côte d'Azur, CNRS, GREDEG, France*
[e] *Institute of Economics, Sant'Anna School of Advanced Studies, Pisa*
[f] *Sciences Po, OFCE, France*

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Abstract

We investigate the structure and evolution of credit growth across Italian provinces. Using an econometric approach based on Random Matrix Theory, we decompose regional credit dynamics into common and idiosyncratic components. We use a longitudinal dataset of credit at the provincial level (NUTS-3 regions) covering the period 2000–2020 and document substantial heterogeneity in the synchronization of credit growth across local economies. Our results suggest that, while aggregate credit growth is largely driven by a strong common component, substantial heterogeneity emerges across disaggregated credit categories. Household mortgage lending displays strong and persistent co-movement across provinces, whereas corporate mortgages and unsecured credit are characterized by higher dispersion and relatively weaker common dynamics. Regional divergence intensifies sharply between 2010 and 2014, coinciding with the European sovereign debt crisis, suggesting a fragmentation of local credit supply and demand. Importantly, divergence does not display any clear geographical pattern, underscoring the role of non-spatial factors in shaping regional credit dynamics.

Keywords: Credit growth, Regional heterogeneity, Local credit markets, Synchronization.
JEL Codes: C38, E51, G21, R12

✉ Claudio Barbieri – claudio.barbieri@ecb.europa.eu.
✉ Mattia Guerini – mattia.guerini@unibs.it
✉ Mauro Napoletano – mauro.napoletano@univ-cotedazur.fr

1 Introduction

The heterogeneous effects of ECB monetary policy within the Euro Area have attracted significant attention, particularly in the aftermath of the sovereign debt crisis and more recently following the inflation surge caused by the Covid-19 pandemic and the Russian invasion of Ukraine.[1] Since the seminal contribution of Mundell (1961), economists have recognized that economic divergences within a currency union can undermine the effectiveness of a common monetary policy. The theory of optimal currency areas suggests that while long-term shocks require regional price and wage adjustments, a common currency and integrated financial markets help absorb temporary shocks (Mundell, 1973; McKinnon, 2004; De Grauwe, 2018). In particular, capital flows are often considered a key mechanism to smooth short-term economic fluctuations (Bayoumi and Rose, 1993). The recent European Commission report of Draghi (2024) has highlighted the importance of capital market integration for EU. Well-integrated capital markets can support more efficient allocation of funds, facilitate investment, and enable the creation and scaling-up of EU companies, which are on average smaller and less financed than their US and Chinese counterparts.

Recent empirical research, however, has challenged the notion that financial integration necessarily promotes regional convergence. Studies such as Martin and Minns (1995); Mackay and Molyneux (1996); Dow and Montagnoli (2007); Dow et al. (2012) highlight that financial centralization can exacerbate regional asymmetries, reinforcing core-periphery dynamics.[2] Empirical evidence on European regional convergence suggests that, even if the European Monetary Union fostered convergence across countries, disparities within countries have often increased (Fatas, 1997; Cuadrado-Roura, 2001; Giannetti, 2002). Overall, emerging synchronization patterns are more complex than theoretical models imply: while national-level clustering is observed, intra-country regional dynamics follow diverse and evolving trajectories (Cuadrado-Roura, 2001).[3]

From a national perspective, more homogeneous growth across different regions can foster positive spillovers and reinforce the uniformity of monetary policy transmission. For instance, a region benefits from positive economic growth in neighboring regions through a potentially higher local demand. Conversely, because regional credit markets are unsegmented, a decline in the credit supply in one region not only reduces funding for local firms but also propagates to surrounding regions, dampening aggregate demand and contracting

[1]See, among others, Boivin et al. (2009); Ciccarelli et al. (2013); Barigozzi et al. (2014); Georgiadis (2015); Boeckx et al. (2017); Burriel and Galesi (2018); Benigno et al. (2022).

[2]Dow et al. (2012) identify three key reasons why regional financial structures could be better at promoting convergence: (i) information asymmetries and transaction costs increase with distance from financial centers (see also Presbitero et al. (2014)); (ii) centralized financial markets reduce local credit availability, disproportionately affecting SMEs, which are often drivers of innovation and growth; (iii) spatial supply and demand dynamics can be self-reinforcing, limiting local economic synergies.

[3]Key factors influencing regional dynamics include urban systems, human capital availability, regional accessibility, advanced production services, institutional quality, social attractiveness, sector specialization, and the presence of large firms in declining industries (Cuadrado-Roura, 2001; Giannetti, 2002).

economic activity (Huber, 2018).

Italy proves a particularly interesting setting to study the heterogeneous effects of monetary policy, given its diverse transmission channels and documented regional disparities (Rungi and Biancalani, 2019; Eichengreen, 2019; Federico et al., 2019). While previous studies have examined the asymmetric effects of monetary policy in Italy (see e.g. Angeloni et al., 1995; Fiorentini and Tamborini, 2001; Dow et al., 2012; Albertazzi et al., 2014; Barigozzi et al., 2014; Doerr et al., 2018), the synchronization and divergence of credit growth across local regions has received relatively little attention. This paper addresses this gap by analyzing Italian credit growth between 2000 and 2020, with a particular focus on the 2012 sovereign debt crisis. Using a novel, confidential database from the *Centrale del Rischio Finanziario* (CRIF), we examine credit growth dynamics at a granular level.

We study credit synchronization using an econometric procedure based on Random Matrix Theory (RMT henceforth; see Potters and Bouchaud, 2020), which allows us to identify statistically significant common factors. Specifically, we construct rolling-window correlation matrices of province-level credit growth and compute their principal components (eigenvalues) and the associated eigenvectors. By comparing the empirical eigenvalues with the theoretical bounds implied by RMT, we filter out noise and isolate genuine common dynamics. The dominant common component, when statistically significant according to RMT bounds, captures aggregate synchronization, while the associated eigenvector loadings measure each province's alignment with the common factor, providing time-varying indicators of convergence and divergence. These measures are then used in panel regressions to examine the macroeconomic determinants of credit co-movement and dispersion.

We find that aggregate credit and household mortgage growth generally exhibit significant synchronization, whereas corporate unsecured credit tends to diverge. At the same time, synchronization may change substantially during crisis times. In particulat, synchronization declined across all asset classes between 2010 and 2012, during the Sovereign Debt Crisis. In contrast, it increased moderately for mortgages during the Covid-19 pandemic but fell sharply for unsecured loans. We also examine the geographical distribution of the eigenvector loadings, which provide information on each province's contribution to the common component and indicate whether local credit dynamics are aligned with the national trend. We find no evidence of a clear structural pattern. Asymmetries in regional credit dynamics do not follow the typical north-south divide observed for many economic variables, suggesting a more fragmented landscape. Finally, regression analysis reveals that post-2012, mortgage growth declined while becoming more synchronized, whereas corporate unsecured credit exhibited increasing divergence. Synchronization patterns are significantly correlated with unemployment and value-added per capita, highlighting the importance of macroeconomic fundamentals in shaping financial cycles (Terrones et al., 2011; Borio, 2014).

Our findings have implications for the literature on regional drivers of growth and for the spatial transmission of common monetary policy in the Eurozone. By quantifying the degree of synchronization in credit dynamics across provinces, our framework sheds light on the relative importance of national versus local forces in shaping regional credit cycles.Understanding regional synchronization and divergence is crucial for assessing the effectiveness of monetary policy, especially during periods of crisis. Regional asymmetries may arise either because localized shocks dominate national trends or because regions respond differently to common shocks (Brunello et al., 2001).

These mechanisms are particularly relevant in Italy. Over the past decade, fluctuations in sovereign spreads have affected banks' balance sheets, given the strong exposure of Italian banks to sovereign debt. Because bank lending plays a central role in the transmission of monetary policy, these shocks may translate into heterogeneous credit dynamics across regions (Bottero et al., 2020). As a result, the common Eurozone monetary policy may translate into heterogeneous credit dynamics not only across countries but also across regions within the same country.

Consistent with this view, our results show that mortgage credit declined relatively uniformly across provinces after the sovereign debt crisis, whereas corporate unsecured credit displayed substantial divergence. Importantly, this divergence does not follow the traditional North–South divide that characterizes many economic outcomes in Italy. Instead, it suggests that province-specific economic conditions and firm characteristics play a more important role than broad geographical divides in shaping regional credit dynamics.[4]

The paper is structured as follows. Section 2 reviews the extant literature on the impact of recent crises on the Italian credit market at the national and regional level. Section 4 details the Random Matrix Theory methodology, while Section 3 presents the database. Section 5 outlines the empirical findings. Section 6 explores the macroeconomic determinants of synchronization. Finally, Section 7 discusses policy implications and future research directions, while Section 8 concludes the paper. An appendix integrates the paper with additional tests for robustness, graphs and tables that for sake of brevity have been excluded from the main text.

[4] Brunello et al. (2001) similarly find that industry location has limited explanatory power for regional unemployment disparities in Italy.

2 Credit, crises and regional asymmetries in the italian economy

The literature relevant to our study can be organized into two complementary strands. The first examines regional asymmetries in the Italian economy, documenting persistent heterogeneity in local economic dynamics and in the transmission of macroeconomic shocks across regions. The second focuses on the evolution of credit in Italy, with particular emphasis on the role of financial and sovereign crises in shaping credit dynamics and generating fragmentation in credit markets. Taken together, these strands highlight the importance of analyzing credit developments through a regional lens, especially in the presence of uneven shock transmission.

2.1 Regional Asymmetries in Italy

Regional disparities in Italy are well documented and display a strong degree of persistence. Barro and Sala-i Martin (1991) show that Italy exhibits the highest dispersion in GDP per capita among the largest European economies, while Brunello et al. (2001) document persistent unemployment differentials and asymmetric wage formation between the North and the South, consistent with Saint-Paul (1997). Differences in industrial composition further shape regional exposure to macroeconomic shocks: manufacturing-intensive and temporary-worker-intensive regions tend to be more vulnerable during downturns, while areas with larger public employment and services sectors are more resilient (Presbitero et al., 2014; Lagravinese, 2015). As a result, a persistent North–South divide emerges across labor markets, exports, innovation, and broader macroeconomic outcomes (Iammarino et al., 2004; Guerrieri and Iammarino, 2007; Evangelista et al., 2002; Mauro, 2004).

Evidence from credit markets mirrors these patterns. Dow et al. (2012) document persistent regional interest rate differentials, showing that convergence at the macro-regional level often masks substantial heterogeneity at the provincial level, in line with the dispersion patterns identified in our analysis.

2.2 Credit Market Developments and Financial Stress in Italy

Italy constitutes a natural laboratory for studying credit and finalcial stress transmission given its bank-centered financial system (Angeloni et al., 1995; Marotta, 1997; Becchetti et al., 2011). Historically, the Italian financial sector has been characterized by limited capital market development, a fragmented banking industry, and low credit market integration. Consumer credit expanded steadily since the 1990s and was highly interest-rate elastic prior to the global financial crisis (Alessie et al., 2005). On the borrower side, the prevalence of small and medium enterprises (SMEs henceforth) and the widespread use of trade credit play a central role.

Marotta (1997) shows that large firms can partially insulate themselves from credit tightening by extending trade credit, while D'Auria et al. (1999) document the role of long-term bank–firm relationships in mitigating information asymmetries, with potentially heterogeneous effects across territories.

Italy was initially shielded from the first phase of the global financial crisis by its traditional financial intermediation model and limited international exposure (Quaglia, 2009; Bonaccorsi di Patti and Sette, 2012). After Lehman's collapse, however, bank profitability and capitalization deteriorated sharply (Angelini et al., 2011), triggering a severe credit contraction. Both supply and demand factors contributed: balance sheet deterioration and rising risk constrained supply (Del Giovane et al., 2011), while weak demand further depressed lending (Panetta and Signoretti, 2010). Banks engaged in a pronounced "flight to quality", disproportionately cutting credit to riskier firms (Albertazzi and Marchetti, 2010), with adverse effects on investment and productivity (Gaiotti, 2011) that also varied across firms and locations.

The sovereign debt crisis marked the most severe phase of distress and made spatial fragmentation particularly salient. Presbitero et al. (2014) document a "home bias" in credit allocation, with banks cutting lending more aggressively to distant firms. The sharp increase in NPL ratios acted as a bank-specific shock, constraining lending and profitability (Accornero et al., 2017), while the resulting credit contraction had persistent real effects on investment and productivity (Doerr et al., 2018; Antonin et al., 2019).

Also during the COVID-19 pandemic, sovereign yield divergence re-emerged but was rapidly contained by large-scale ECB interventions, notably the PEPP (Moessner and de Haan, 2022; Barbieri et al., 2024). Fiscal and monetary measures mitigated financial fragmentation (Corradin et al., 2021; Ortmans and Tripier, 2020; Jinjarak et al., 2021), although monetary transmission weakened (Wei and Han, 2021) and observed convergence partly reflected rising yields in low-debt countries (Fendel et al., 2021). Credit guarantees proved effective in sustaining lending and limiting regional disparities in credit access (Granja et al., 2020; Kozeniauskas et al., 2020; Core and De Marco, 2021; Gourinchas et al., 2021; Altavilla et al., 2021; Barbieri et al., 2022).

Overall, the literature documents persistent heterogeneity in the Italian credit market across banks, firms, and regions, amplified during crisis episodes. SMEs remain highly dependent on bank credit, and lending adjustments exhibit strong spatial components. Building on this evidence, we now turn to our methodology for measuring and characterizing within-country credit divergence.

3 Description of the data

We use confidential data provided by Centrale Rischi Finanziari (CRIF) that report monthly amounts of credit granted in Italy at the provincial level from January 2000 to March 2020. The current administrative organization of Italy consists of 107 provinces, allowing us to capture fine-grained spatial variation in credit dynamics within the country. This high level of geographical disaggregation is particularly well suited to studying regional heterogeneity and within-country divergence in credit growth.

The database is detailed by loan type, borrower type, and classifications based on loan duration and amount (Table 1).[5] Loans are classified into two main categories: mortgages and unsecured loans, see Figure 1 (a). Mortgages account for the largest share of total credit, peaking at around 9 trillion in 2007 and stabilizing at around 6 trillion between 2015 and 2020. Following the sovereign debt crisis, mortgage volumes declined sharply, reaching approximately 3 trillion between 2012 and 2015. Unsecured loans display a persistent upward trend, remaining above 3 trillion from 2017 onward, although their growth slowed markedly between 2011 and 2013. The increasing importance of unsecured lending in Italy has also been documented by Alessie et al. (2005).

	Mortgages	**Unsecured loans**
Borrower classes	Households; Individual firms; Companies	
Duration classes (years)	0-10; 10-20; 20-30; >30	0-1; 1-2; 2-3; 3-4; 4-5; >5
Amount classes (€ 1000)	0-75; 75-100; 100-150; 150-300; >300	0-5; 5-10; 10k-20; 20-35; 35-75; >75

Table 1: Structure of the CRIF data

Regarding mortgages, the majority of credit is granted to households – see Figure 1 (b). Household mortgage volumes rose to nearly 5.5 trillion in 2007 before declining during the global financial crisis (GFC), falling from around 4.5 trillion in 2011 to approximately 2 trillion. From 2014 onward, housing lending recovered, rising above 4 trillion and remaining stable until 2020.

Companies also received a significant portion of mortgage lending, particularly between 2007 and 2011, when corporate mortgage volumes surpassed 2 trillion (about one-third of the total). After 2010, corporate volumes declined to approximately 1.5 trillion and, unlike household mortgages, did not recover after 2012, remaining broadly stable. These dynamics suggest that household and corporate credit responded differently to financial shocks, potentially generating heterogeneous regional effects in local credit markets.

A smaller fraction of mortgages is granted to individual firms, which in the Italian legal framework correspond to businesses whose owners are personally liable for company debts and which are typically small in size. Mortgages to individual firms amount to less than €1 trillion (around one-tenth of total mortgages) and

[5] For our main analysis, we aggregate credit volumes by amount category, while the other dimensions are used for more granular investigations.

follow a trend similar to that of household and corporate mortgages, declining between 2010 and 2015, albeit on a smaller scale.

Unsecured loans are predominantly granted to companies as visible from Figure 1 (c). The volume of unsecured loans grew in two main phases: first, from 2000 to 2010, reaching roughly 1.5 trillion, and then after 2014, peaking at nearly 3 trillion in 2018. Between 2012 and 2014, growth stalled, with volumes slightly above 1 trillion for three years before accelerating again in 2014. This pattern highlights the cyclical nature of unsecured lending and may strongly contribute to heterogeneous credit dynamics across regions.

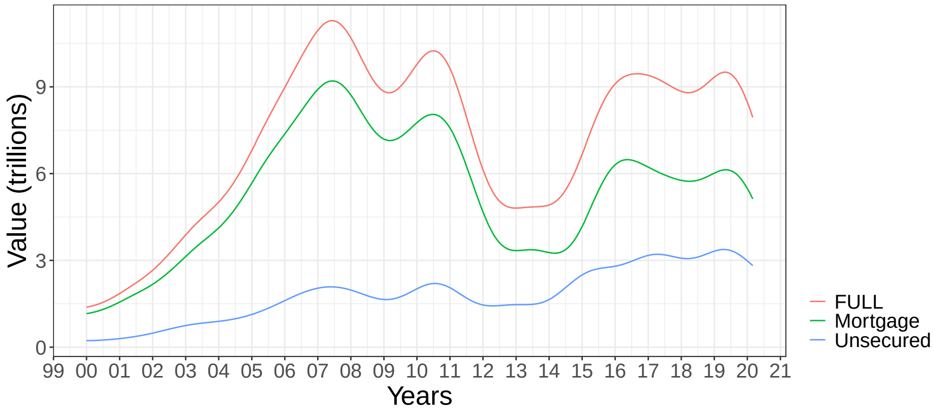
Unsecured loans to households and individual firms remains relatively small compared with lending to companies and exhibits a more stable trend over time. Prior to 2010, household volumes exceeded those of individual firms. After 2011, household unsecured lending declined and stabilized, whereas lending to individual firms grew slightly, overtaking household lending following the sovereign debt crisis.

To examine loan composition by duration, we distinguish between mortgages shorter and longer than twenty years and unsecured loans shorter and longer than four years (Figure 2). Short-term mortgages consistently exceeded long-term ones by about 1 trillion euros for most of the sample period – see Figure 2 (a), with the gap narrowing only in 2019, when both categories stabilized around € 3 trillion. Mortgage volumes follow an "M-shaped" pattern: peaking in 2007, declining afterward, rising again between 2014 and 2016, and stabilizing at approximately € 3 trillion from 2016 onward. By 2020, both long- and short-term mortgages remained below pre-crisis levels.

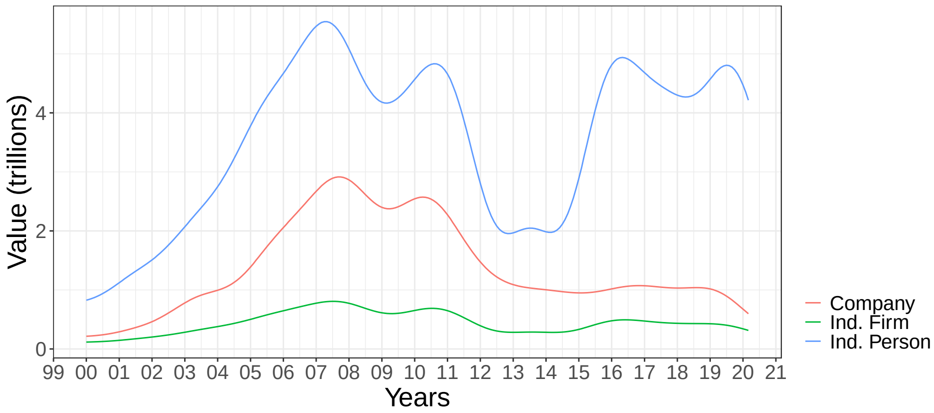
Long-term unsecured loans exceeded short-term loans until 2014, when short-term loans began growing faster and eventually converged with long-term volumes – see Figure 2 (b). Both categories followed an overall upward trend until 2020, despite a slowdown between 2011 and 2014. Notably, short-term unsecured loans nearly doubled in 2014, outpacing growth in long-term loans. From 2016 onward, both categories stabilized at around 1.5 trillion, indicating that the post-crisis growth in unsecured loans was primarily driven by an increase in short-term lending.

Before analyzing credit synchronization across provinces, we first summarize the main descriptive changes in credit volumes during the sovereign debt crisis and the Covid-19 pandemic. The sovereign debt crisis had a substantial but temporary effect on household mortgages. By contrast, corporate mortgage volumes declined in 2010 and remained less than half of the pre-crisis levels recorded between 2006 and 2010. Unsecured loans to companies, however, contracted only mildly after 2010 and grew steadily until 2019, suggesting a possible substitution between mortgages and unsecured loans in corporate financing.

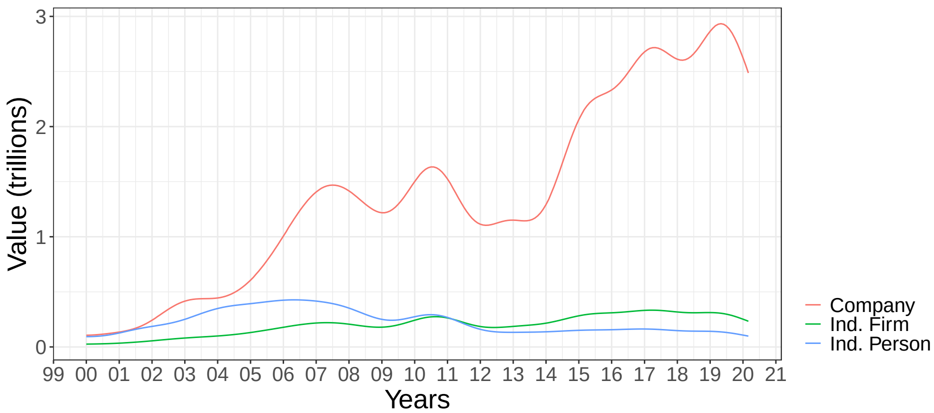
During the Covid-19 pandemic, unsecured loans to companies surged from 3 to 5 trillion, likely reflecting government-guaranteed loan schemes, before declining after 2020. Household mortgage volumes increased



(a) Volumes of total lending, mortgages, and unsecured loans



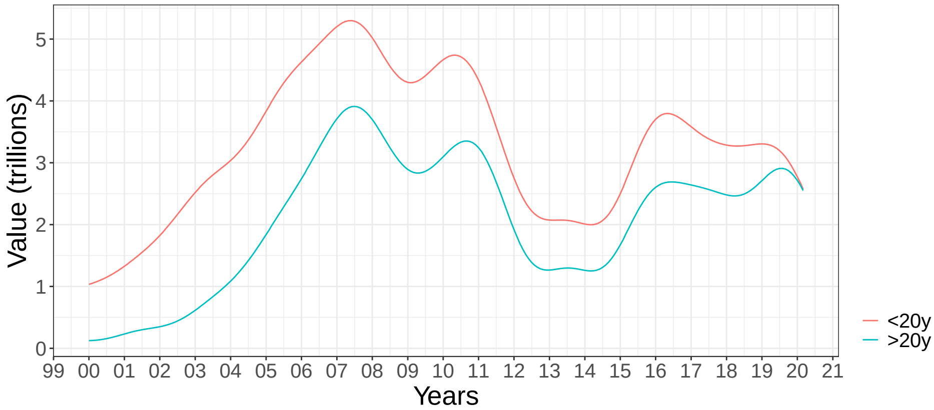
(b) Composition of mortgages



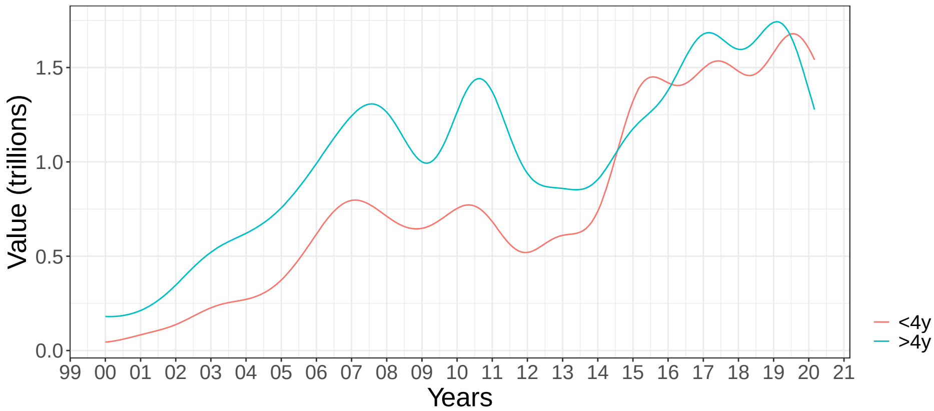
(c) Composition of unsecured loans

Figure 1: Description of bank credit lending in Italy from 2000 to 2022

only moderately and did not exhibit the same sharp dynamics. Loan duration patterns also shifted: long-term mortgages, previously lower than short-term mortgages, increased, while short-term volumes declined.



(a) Composition of mortgages by duration



(b) Composition of unsecured loans by duration

Figure 2: Volume of bank credit lending by duration

Similarly, growth in unsecured loans was driven mainly by maturities longer than four years. From 2018 onward, total mortgage volumes remained stable, but their composition shifted toward longer maturities.

The descriptive evidence presented so far is aggregated and preliminary, and does not allow for an assessment of provincial and regional patterns, which are analyzed in depth in Section 5 using the methodology described in the next section.

4 Methodology

The method we employ to study the synchronization of credit growth across Italian provinces selects principal components using random matrix theory (RMT) (Bouchaud and Potters, 2015; Laloux et al., 2000; Guerini et al., 2019; Barbieri et al., 2024). This approach allows one to identify which principal components extracted from a set of provincial time series contain statistically meaningful, non-spurious information.[6]

Once the significant principal components are identified, they are used in two subsequent analytical steps. First, we analyze the eigenvector components associated with each principal component, which provide information on the structure of co-movements across provinces. This step helps to identify clusters of local areas that are more strongly or weakly correlated with the national credit cycle. Second, we extract the common component and use the associated loadings to characterize how provincial credit dynamics co-move, thereby clarifying whether provincial credit dynamics move pro- or counter-cyclically with respect to the common component.

4.1 Principal Component Analysis

Given our set of stationary time series of credit growth rates, we perform a Principal Component Analysis (PCA) on overlapping rolling windows. Each rolling window $\underset{K\times N}{X}$ corresponds to a subsample of dimensionality $K < T$ drawn from the full database $\underset{T\times N}{X}$ of stationary time series (growth rates of credit variables in our sample). When moving from one window to the next, observations are updated by a fixed *step* S – i.e., S observations are removed from the beginning of the window and S new observations are added at the end.

By construction, smaller windows allow for a more precise tracking of synchronization over time. At the same time, the window length must be sufficiently large to ensure that the estimated correlation coefficients are statistically meaningful and not driven by high-frequency outliers. We therefore fix the length of each window to one year and the step size to one quarter. As a result, two consecutive rolling windows overlap for three months out of twelve. This choice balances temporal resolution and statistical reliability, allowing us to closely monitor the evolution of the principal components by updating only a limited amount of information at each step.[7]

For each rolling window, we compute the matrix of Pearson correlation coefficients, denoted by E, as follows:

$$E = \frac{1}{K}\tilde{X}^T\tilde{X} \tag{1}$$

where $\underset{K\times N}{\tilde{X}}$ is the demeaned and standardized version of $\underset{K\times N}{X}$, and $(\cdot)^T$ denotes the transpose operator. The resulting matrix E has dimension $N \times N$. Each element $e_{i,j}$ measures the correlation between the credit growth rates of provinces i and j within a given rolling window $w \in 1,\ldots,W$, where W denotes the total number of windows.

[6]Principal components are based on correlations between time series, which in finite samples may also arise by chance and therefore be spurious. See also Section 4.2.

[7]We check the robustness of our results to alternative values of the length and step parameters of the rolling windows. These additional results are available upon request.

Being symmetric and positive semi-definite, the matrix E admits a spectral decomposition into non-negative eigenvalues and their associated eigenvectors. Each eigenvalue λ_i corresponds to a principal component, defined as a linear combination of the original provincial series, and captures a specific share of the total variance in credit growth. In this framework, the largest eigenvalues reflect common patterns of co-movement across provinces, while smaller eigenvalues are associated with more localized or idiosyncratic dynamics.

4.2 Random Matrix Theory and Factors Selection

Random Matrix Theory (RMT) provides a criterion to select only those principal components that contain information beyond what can be attributed to purely spurious fluctuations.[8] With the term "spurious fluctuations", we do not refer to the correlation between non-stationary $I(1)$ variables, but rather to the fact that even two stationary $i.i.d.$ series, when observed over a finite sample, may display non-zero correlations purely by chance.

The key issue, therefore, is how to assess whether the empirical distribution of correlations reflects genuine common dynamics or is instead compatible with what would be observed in a finite sample of independent random variables. RMT addresses this issue by comparing the empirical correlation matrix with the theoretical properties of correlation matrices generated by a random normal model.

A central result in this framework is the theorem by Marčenko and Pastur (1967), which characterizes the probability density function of the eigenvalues of a random correlation matrix constructed from independent and identically distributed normal series. According to this result, eigenvalues are asymptotically distributed according to the Marčenko-Pastur distribution (see Marčenko and Pastur, 1967; Laloux et al., 1999).

Theorem - Marčenko-Pastur law. *For $N, T \to \infty$ and $Q = \frac{T}{N} \to a > 1$, the density function of the eigenvalues of $\hat{\Sigma}$ is given by*

$$\rho\hat{\Sigma}(\lambda) = \begin{cases} \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_{max}^{rmt} - \lambda)(\lambda - \lambda_{min}^{rmt})}}{\lambda} & \textit{for } \lambda \in (\lambda_{min}^{rmt}, \lambda_{max}^{rmt}) \\ 0 & \textit{else} \end{cases} \tag{2}$$

where $\lambda_{max/min}^{RMT} = \sigma^2 \left(1 \pm \sqrt{\frac{1}{Q}}\right)^2$ are the upper/lower bounds of the eigenvalues associated with a random matrix with the same variance σ^2 and the same Q of the empirical observations.

Thus, any empirical eigenvalue lying within the bounds of the theoretical Marčenko–Pastur distribution is

[8] Since factor models can be estimated through principal components (Stock and Watson, 2002; Onatski, 2010), our method can also be used for factor selection. For an application and discussion, see (Barbieri et al., 2024).

interpreted as reflecting variance that can be generated by a purely random correlation structure. In this case, observed co-movements are indistinguishable from spurious correlations arising from finite-sample noise. By contrast, eigenvalues falling outside these bounds are associated with genuine common dynamics driving co-movements among the variables of interest.

However, since the Marčenko–Pastur law is derived under asymptotic assumptions, we complement the analytical bounds with Monte Carlo simulations. Specifically, we compute the Marčenko–Pastur boundaries from simulated random correlation matrices and compare them with the empirically estimated eigenvalues. This procedure allows us to assess whether the cross-sectional dimension N is sufficiently large for the asymptotic approximation to be reliable in our empirical setting.[9]

4.3 Measuring synchronization

An additional statistic summarizing the extent to which co-movements deviate from a purely random correlation structure is the *Inverse Participation Ratio* (IPR) associated with each eigenvalue i. The IPR is defined as:

$$IPR_i = \sum_{j=1}^{N} u_i(j)^4 \tag{3}$$

where $u_i(j)$ denotes the j^{th} element of the eigenvector associated with the i^{th} eigenvalue.[10]

The IPR_i provides a compact measure of how many variables (i.e. how many provinces) contribute significantly to a given eigenvalue (i.e., the national common factor). It is continuous and bounded in the interval $\frac{1}{N} \leq IPR_i \leq 1$: lower values indicate that the corresponding eigenvector is broadly distributed across provinces, while higher values signal that co-movement is driven by a small subset of units. In particular, the IPR attains two polar cases that are useful for interpretation:

$$IPR_i = \begin{cases} 1/N & \iff \quad u_i(j)^2 = \frac{1}{N} \quad \forall j \\ 1 & \iff \quad u_i(j)^2 = 0 \quad \forall j \text{ but one.} \end{cases}$$

When $IPR_i = 1/N$, all N variables contribute equally to the i^{th} eigenvalue, representing a perfectly synchronized system across provinces. At the opposite extreme, when $IPR_i = 1$, the i^{th} eigenvalue is driven by a single variable, indicating highly localized co-movement and a state of extreme asynchronicity. Although these polar cases are unlikely to occur in real-world applications, they provide useful theoretical benchmarks

[9] We carry out additional robustness checks on the Marčenko–Pastur boundaries in Appendix B. In particular, we test (i) a heavy-tail random $i.i.d.$ model, which accounts for the presence of extreme values in the series (Appendix B.1); and (ii) a rotational random shuffling procedure to address potential residual autocorrelation in the stationary time series (Appendix B.2).

[10] The fourth power is required because, for positive semi-definite symmetric matrices (such as covariance or correlation matrices), the eigenvectors are normalized so that $\sum_{j=1}^{N} u_i(j)^2 = 1$.

to assess the degree of regional synchronization.

5 Results

This section presents the main results on credit synchronization across Italian provinces based on random matrix theory (RMT). We begin by examining the spatial distribution of credit across provinces, which provides the geographical context for the subsequent analysis and allows us to assess the extent of regional heterogeneity in credit allocation. We then identify the significant eigenvalues (Figure 5) and analyze the corresponding eigenvectors (Figures 7–8 and 9) to uncover the dominant synchronization patterns and their spatial configuration.

Following the structure outlined in Section 3, we first consider the time series of aggregate mortgages and unsecured loans at the provincial level. We then investigate synchronization patterns across borrower types, and finally examine heterogeneity in synchronization by loan duration.

Synchronization is defined according to two empirical criteria. First, for a set of provincial time series to be considered synchronized, the largest principal component (i.e., the largest eigenvalue of the standardized matrix of credit growth rates) must account for a substantial share of total variance (approximately two-thirds). This condition ensures the presence of a dominant common factor driving co-movement across provinces. Second, the eigenvector components associated with the largest principal component should approximate a continuous uniform distribution, implying that all provinces contribute relatively evenly to the common dynamic.

If either condition is not satisfied, we classify the system as divergent. When more than one principal component is significant according to RMT, the data reveal the presence of distinct clusters of provinces, indicating segmented co-movement patterns rather than a single nationwide dynamic. Alternatively, if the loadings of the first principal component are highly heterogeneous, the observed co-movement reflects primarily a subset of provinces, suggesting partial integration rather than broad-based convergence.

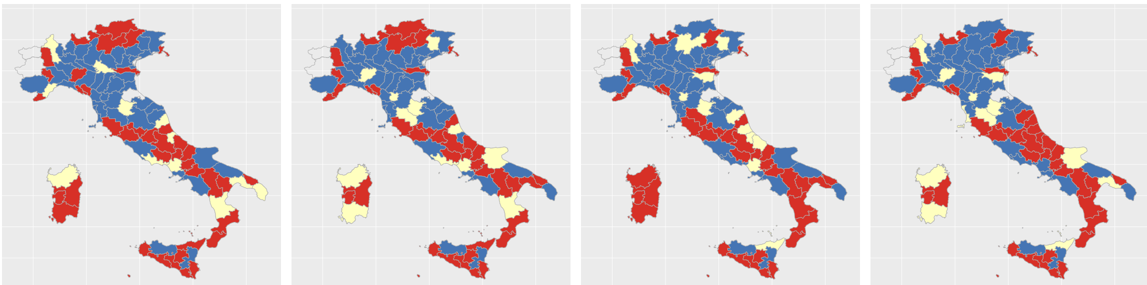
5.1 Maps of Italian credit dynamics

A descriptive analysis of the geographical distribution of italian credit dynamics provides the spatial structure for our synchronization analysis. Figures 3 and 4 report the distribution of credit shares and credit growth across provinces, respectively. Since Milan and Rome account for approximately 20% of total credit, direct visual comparisons with other provinces may be misleading. We therefore group provinces into three categories based on their rankings in terms of national credit share and credit growth, in order to highlight meaningful spatial differences.

The distribution of credit shares across provinces has remained relatively stable over time (see Figure 3). The 40 provinces with the largest credit shares are concentrated in the North and Center-North, both along the eastern and western corridors, as well as along the western coast (including Rome and Naples). By contrast, the 40 provinces with the smallest credit shares are predominantly located in the Center, the South and the islands, although several north-eastern provinces also fall into the lower-share group. This pattern points to a persistent spatial concentration of credit in economically stronger areas.

If provinces with lower credit shares were systematically recording faster credit growth, one might expect a gradual convergence process leading to a more balanced territorial distribution of credit. However, this does not emerge from the data. The credit growth map reveals more fragmented and time-varying dynamics (Fig. 4). The 40 provinces with the highest credit growth are geographically dispersed across the country. Unlike credit shares, growth rankings change markedly over time. For example, north-eastern provinces display stronger credit growth in 2000–2005 and 2015–2020, but weaker growth in 2011–2015, while several central provinces exhibit the opposite pattern.

Overall, these shifting growth dynamics suggest the absence of regional convergence in credit. Instead, credit expansions appear episodic and spatially heterogeneous. We therefore turn to the synchronization analysis to assess whether, beneath this apparent heterogeneity, a common national dynamic prevails or whether provincial credit cycles remain structurally segmented.



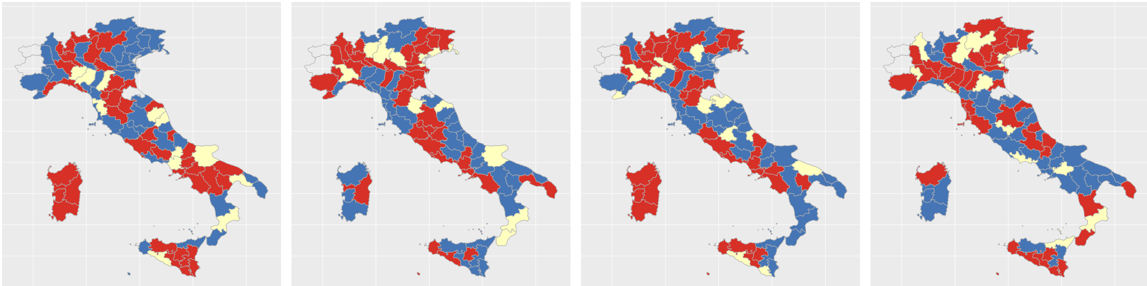
(a) 2000-2005 **(b)** 2006-2010 **(c)** 2011-2015 **(d)** 2016-2020

Figure 3: Italian provinces with high (blue), medium (yellow), and low (red) shares of total national credit

5.2 Synchronization and divergence in credit dynamics

We begin by examining the co-movement of credit growth, both at the aggregate level and for unsecured loans. These two cases illustrate, respectively, clear examples of synchronization and divergence according to the empirical criteria introduced above.[11]

[11]Figure 6 presents the absorption ratios, which measure the fraction of variance explained by the principal components. These are calculated for the three largest components, as all remaining components lie below the RMT boundary and therefore capture co-movements statistically indistinguishable from random noise. Complete results from the RMT analysis are reported in Appendix A. Figure A.1 provides an overview of the RMT comparison, Figure A.2 reports the IPR values, and Figure A.3 shows the standard deviation of the eigenvector components associated with the largest eigenvalue.



(a) 2000-2005 **(b)** 2006-2010 **(c)** 2011-2015 **(d)** 2016-2020

Figure 4: Italian provinces with high (blue), medium (yellow), and low (red) credit growth

We find strong evidence of synchronization for total credit growth (Fig. 5a). The largest principal component explains approximately two-thirds of total variance (Fig. 6a), indicating the presence of a dominant common factor driving provincial credit dynamics. No additional principal component is statistically significant relative to the random null model, suggesting the absence of structurally distinct clusters of provinces.

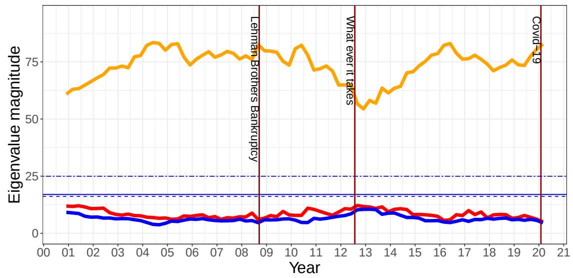
This interpretation is reinforced by the analysis of the inverse participation ratio (IPR, Fig. 5b), which is close to its theoretical lower bound corresponding to a uniformly distributed dynamic. In other words, the contribution of provinces to the common component is relatively even. Consistently, the standard deviation of the eigenvector components remains moderate, indicating that the observed synchronization is not driven by a small subset of large or financially dominant provinces.

In contrast to total credit growth, the dynamics of unsecured loans exhibits substantial divergence across provinces. The largest principal component explains only about one-third of total variance (see Fig. 6b), signaling a much weaker common dynamic across provinces. Additionally, a second significant principal component emerges in some time windows. Even when not systematically significant, this second component accounts for roughly 20

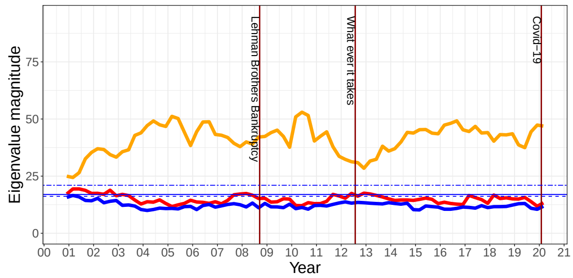
Furthermore, the IPR of unsecured loans is approximately 0.014 (Fig. 5d), which, following the definition in Section 4.3, corresponds to an effective participation ratio of about 70 provinces out of 107. While a majority of provinces contribute to the primary component, a non-negligible share displays limited involvement in the dominant co-movement. Moreover, the eigenvector components for unsecured loans are significantly more heterogeneous than those for total credit, with a standard deviation of around 0.05 compared to approximately 0.025 for total credit.

Taken together, these findings indicate that unsecured loan growth does not follow a uniform national trajectory. Rather, it reflects a structurally segmented territorial dynamic, with different groups of provinces exhibiting partially distinct credit cycles.

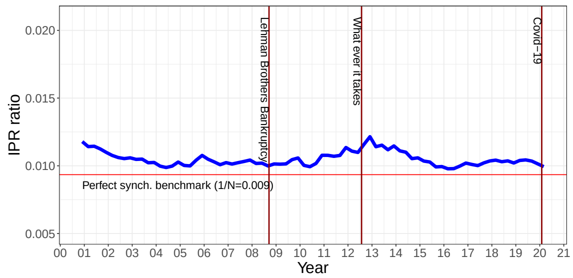
The divergence in unsecured loan growth motivates a deeper analysis of synchronization in aggregate



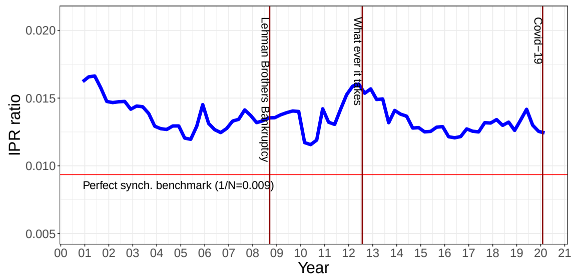
(a) Total credit. Solid line: Marčenko–Pastur theoretical RMT boundary; dashed line: Monte Carlo–simulated boundary; dotted line: RMT boundary under random rotational shuffling



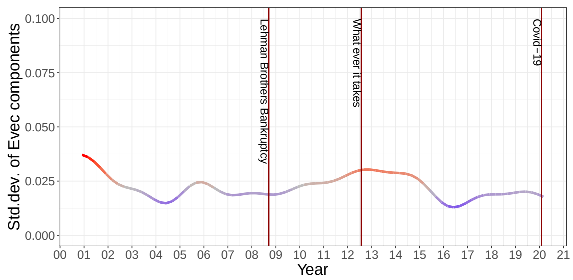
(b) Unsecured loans. Solid line: Marčenko–Pastur theoretical RMT boundary; dashed line: Monte Carlo–simulated boundary; dotted line: RMT boundary under random rotational shuffling



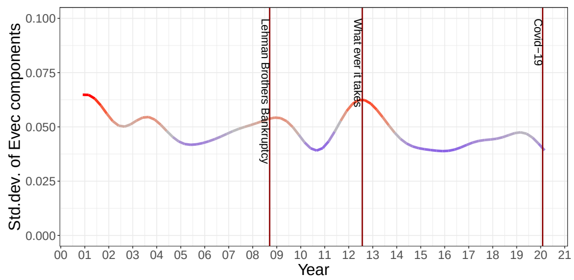
(c) IPR - total credit



(d) IPR - unsecured loans



(e) Std. deviation of eigenvector components - total credit



(f) Std. deviation of eigenvector components - unsecured loans

Figure 5: Empirical measures of synchronization and divergence

credit. Given that mortgages account for the largest share of total credit in Italy (see Section 3), their dynamics are likely to be a key driver of aggregate co-movement.

Consistent with this expectation, mortgage growth exhibits a high degree of synchronization (Fig. 6c). A more disaggregated analysis, however, reveals that this pattern depends crucially on borrower type: mortgages are predominantly extended to households, while a smaller—though still sizeable—share (approximately one-third) is granted to firms.

This distinction proves decisive. Mortgage growth to households exhibits even stronger synchronization than aggregate credit, with the first principal component explaining, on average, around 75% of total variance. By contrast, mortgage growth to firms resembles unsecured lending and displays clear signs of divergence (Fig. 6d and 6f), as the leading component accounts for only about 25% of total variance.

A related question is whether loan maturity contributes to the observed patterns of synchronization and divergence. To address this issue, we analyze mortgages and unsecured loans at short- and long-term maturities.

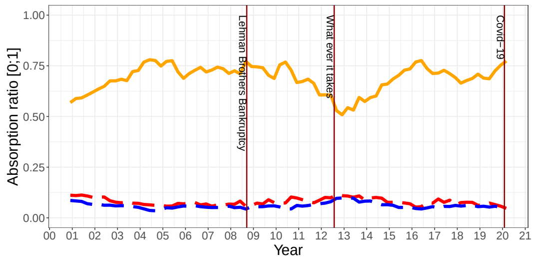
For mortgages, the evidence points to limited differences across maturities. Both short- and long-term loans display synchronization, with the largest principal component explaining roughly half of total variance (Figs. 6g and 6h). No additional components are statistically significant, and indicators of divergence—such as the IPR and the standard deviation of the eigenvector components—remain low. This suggests that maturity structure does not materially alter the broadly integrated dynamic observed for mortgage credit. At the opposite, unsecured loans exhibit divergence irrespective of maturity. For both short- and long-term categories, the largest principal component accounts for less than one-third of total variance (Figs. 6i and 6j), and the distribution of variance across components remains comparatively dispersed.

These findings suggest that the strong national synchronization observed in aggregate credit is largely driven by household credit in the form of mortgages, whereas credit to firms remains considerably more geographically heterogeneous. These patterns hold regardless of loan maturity.

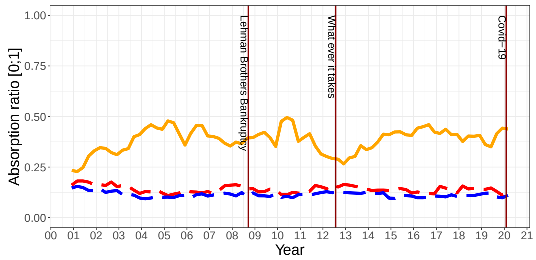
Finally, we examine how credit synchronization evolved during the Sovereign Debt Crisis and the Covid-19 pandemic, two major shocks with potentially asymmetric territorial effects.

During the sovereign debt crisis, the RMT analysis reveals a pronounced U-shaped pattern in the largest principal component between 2010 and 2015 (Fig. 6).[12] Synchronization weakened markedly in the initial phase of the crisis, indicating increased territorial dispersion in credit dynamics, and began to recover after 2012. This evidence is consistent with Barbieri et al. (2024), who document a similar U-shaped evolution in European bond yields and associate the restoration of synchronization with the ECB's unconventional

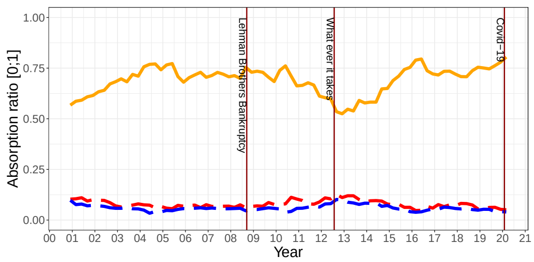
[12]This pattern is corroborated by corresponding peaks in the IPR (Fig. A.2) and in the standard deviation of the eigenvector components (Fig. A.3) over the same period.



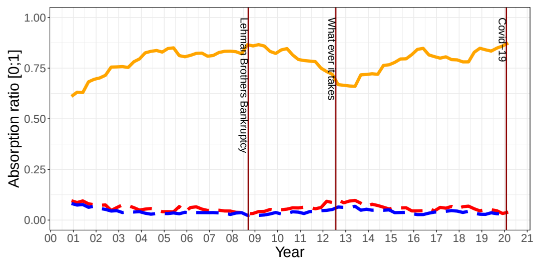
(a) Total credit



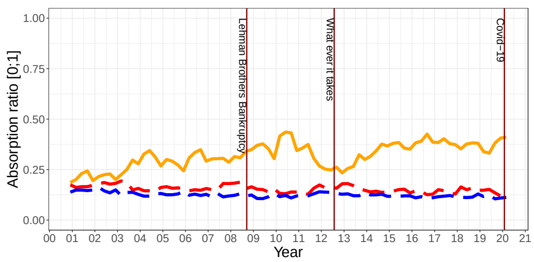
(b) Unsecured loans



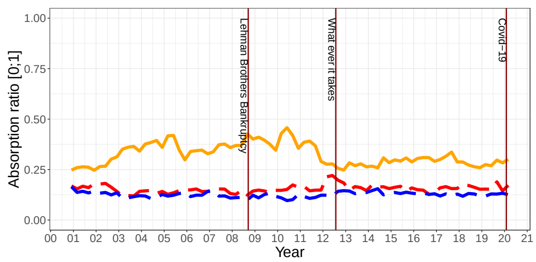
(c) Mortgages



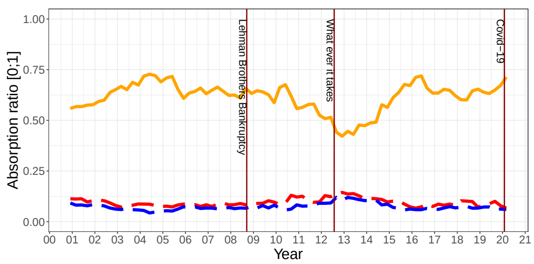
(d) Mortgages to households



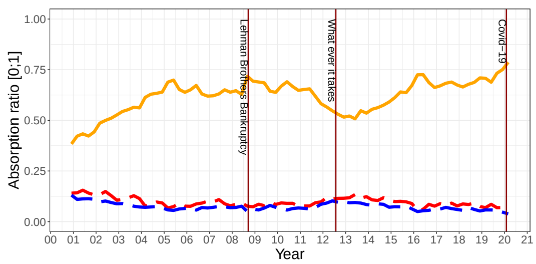
(e) Unsecured loans to company



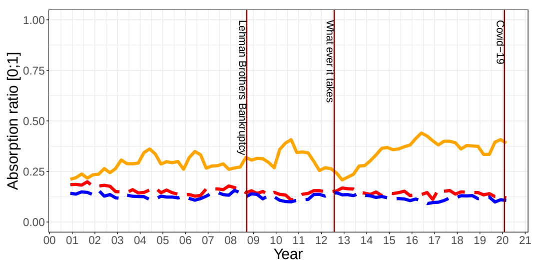
(f) Mortgages to company



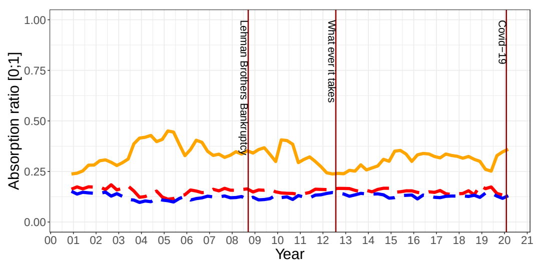
(g) Mortgages, maturity below 20 years



(h) Mortgages, maturity above 20 years



(i) Unsecured loans, maturity below 4 years



(j) Unsecured loans, maturity above 4 years

Figure 6: Absorption ratio

monetary policy measures. However, our results indicate that synchronization did not uniformly return to pre-crisis levels. Household mortgage growth regained and maintained a high degree of synchronization after 2015, whereas corporate mortgage growth remained persistently less synchronized than before the crisis (Fig. 6f), suggesting a more durable geographical segmentation in firm-level credit.

5.3 How do regions contribute to synchronization and divergence?

A central result of the previous section is that, while total credit dynamics are synchronized across Italian provinces, individual credit components are not, with firm credit exhibiting substantially greater divergence than household credit. This also raises the question of whether provinces contribute differently to these patterns of synchronization and divergence, and whether distinct regional clusters can be identified in this respect, possibly reflecting the well-known North–South divide in the Italian economy.

To address this issue, we analyze the eigenvector components associated with the dominant common factor. These components measure the extent to which provincial credit growth loads onto the aggregate dynamic. Provinces with larger weights are more closely aligned with the common trajectory, whereas smaller weights identify provinces whose credit dynamics are more idiosyncratic, thereby contributing to spatial fragmentation.

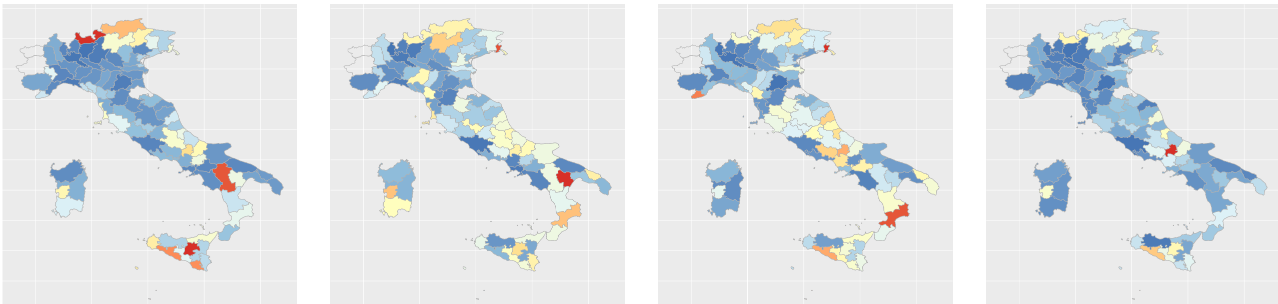
For aggregate loans (Fig. 7), previously identified as strongly synchronized, only a limited number of provinces deviate from the main common component. These episodes of divergence are sporadic and concentrated in specific periods, rather than reflecting stable territorial clusters. This pattern suggests that departures from synchronization represent temporary deviations rather than structurally segmented regional dynamics.

A closer examination of the most divergent credit segments, namely unsecured loans (Fig. 8) and mortgages to companies (Fig. 9), confirms the presence of a larger set of provinces with weak alignment to the common factor. However, their spatial distribution does not conform to a recognizable macro-regional pattern. We find no systematic divergence along the traditional North–South divide, nor a consistent differentiation between the North-West and the North-East. Provinces in Central Italy and the islands likewise alternate between synchronization and divergence, without displaying stable territorial groupings over time.

Taken together, these results indicate that credit growth divergence in Italy does not map neatly onto established geographical cleavages. Rather than reflecting fixed regional blocs, divergence appears to be episodic and cross-cutting, suggesting that provincial credit dynamics are shaped by factors other than broad spatial location.

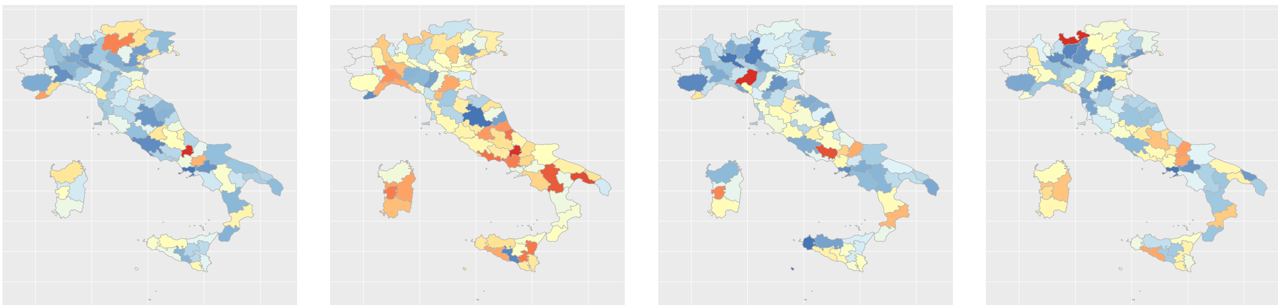
Further insights emerge from the sovereign debt crisis period between 2011 and 2014. First, the number of diverging provinces peaks in 2012 before gradually declining in subsequent years (see Fig. 7 for aggregate loans, Fig. 8 for unsecured loans, and Fig. 9 for mortgages to companies). This temporal pattern mirrors the U-shaped evolution in synchronization identified earlier, with the lowest degree of co-movement observed in 2012.

Second, no clear geographical configuration emerges during the crisis. Divergence in provincial credit growth is not concentrated within a specific macro-region but is instead dispersed across the national territory. The absence of stable territorial clustering suggests that the crisis-induced fragmentation of credit dynamics did not align with established regional divides. Rather than reinforcing pre-existing spatial cleavages, the shock appears to have generated a broadly distributed increase in provincial heterogeneity.



(a) 2011 **(b)** 2012 **(c)** 2013 **(d)** 2014

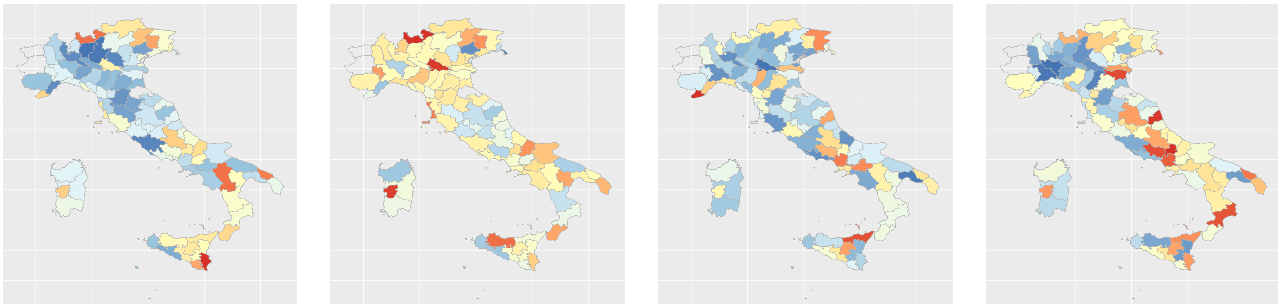
Figure 7: Geographical synchronization of total credit (mortgages and unsecured loans) between 2011 and 2014.
Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the dominant co-movement.



(a) 2011 **(b)** 2012 **(c)** 2013 **(d)** 2014

Figure 8: Geographical synchronization of unsecured loans between 2011 and 2014. Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the dominant co-movement.

A similarly dispersed configuration emerges in the period 2018–2021, particularly during the Covid-19 pandemic. In 2020, unsecured loans exhibited a temporary increase in synchronization (Fig. 11), plausibly reflecting the uniform implementation of government-backed credit support measures across provinces. By contrast, mortgages to companies remained persistently divergent (Fig. 12), in line with the earlier evidence



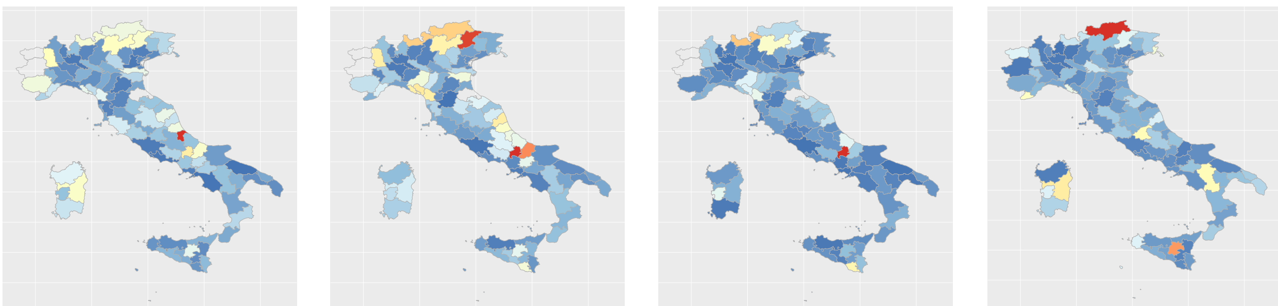
(a) 2011 **(b)** 2012 **(c)** 2013 **(d)** 2014

Figure 9: Geographical synchronization of mortgages to company between 2011 and 2014. Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the dominant co-movement.

that the pandemic did not substantially alter the structural fragmentation of this credit segment.

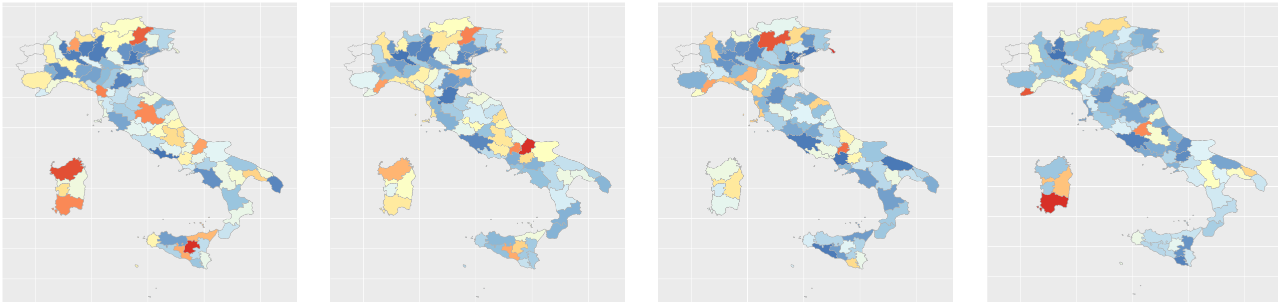
More generally, during the Covid-19 period provinces diverge only intermittently, and these fluctuations cannot be systematically associated with fixed geographical clusters. As in the sovereign debt crisis, no stable territorial configuration of divergence emerges.

The absence of a persistent geographical structure carries two implications. First, credit divergence in Italy cannot be straightforwardly mapped onto traditional macro-regional divides. Second, patterns of synchronization and divergence may differ across spatial scales: national co-movement can coexist with regional or sub-regional heterogeneity. The evidence therefore points to drivers that operate beyond broad spatial location. Prior studies emphasize, for example, the role of sectoral specialization, institutional quality, and firm characteristics in shaping regional financial dynamics Cuadrado-Roura (2001); Giannetti (2002).



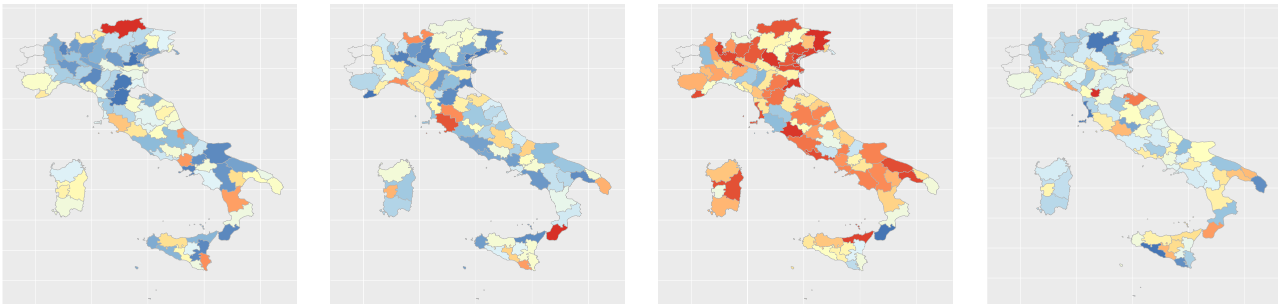
(a) 2018 **(b)** 2019 **(c)** 2020 **(d)** 2021

Figure 10: Geographical synchronization of total credit (mortgages and unsecured loans) between 2018 and 2021.
Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the largest co-movement.



(a) 2018 (b) 2019 (c) 2020 (d) 2021

Figure 11: Geographical synchronization of unsecured loans between 2011 and 2014. Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the largest co-movement.



(a) 2018 (b) 2019 (c) 2020 (d) 2021

Figure 12: Geographical synchronization of mortgages to company between 2011 and 2014. Note: Blue provinces indicate larger eigenvector components, thus more synchronized provinces.; red provinces have lower eigenvector components and thus diverge from the largest co-movement.

6 Drivers of credit divergence

The results in the previous section indicate that credit market fragmentation is neither spatially clustered nor temporally stable. Moreover, episodes of financial stress reshape credit dynamics in ways that differ across asset classes and borrower types. In particular, unsecured lending to firms displays persistent divergence during periods of heightened sovereign bond tensions. In what follows, we formally assess these relationships while controlling for province-specific economic characteristics.

To examine the drivers of credit dispersion and to assess the policy relevance of our divergence measure, we estimate a fixed-effects panel regression model in which the dependent variable is given by the provincial eigenvector components. The explanatory variables are drawn from official statistics provided by the Italian Statistical Institute (IstatData) and capture key structural and economic features of local economies.

A limitation of the analysis is that provincial data are available only at annual frequency for the period 2000–2019. As a result, the model cannot be estimated at higher frequency nor extended to the Covid-19 episode. Despite this constraint, the empirical framework allows us to identify the main structural correlates of credit divergence, with particular reference to the sovereign debt crisis period.

Our dependent variable is defined as the fourth power of the yearly average of the eigenvector components computed for each province. This transformation maintains a direct connection with the synchronization framework, since the IPR (Eq. 3) is defined as the sum of the fourth powers of the eigenvector components and is bounded between 1 (complete divergence) and $1/n$ (perfect synchronization). Accordingly, larger values of the dependent variable indicate a weaker alignment with the dominant common factor. A positive regression coefficient can therefore be interpreted as evidence that the corresponding explanatory variable is associated with greater provincial credit dispersion.[13]

The main explanatory variable is a binary indicator equal to 1 for years from 2012 onward and 0 otherwise, capturing the post-crisis period. This specification allows us to test whether the sovereign debt crisis is associated with a structural shift in provincial credit synchronization. As additional controls, we include value added per capita, export volume, the unemployment rate, a measure of financial risk, and the number of registered firms in each province.[14] Summary statistics for all variables are reported in Table C.

The estimation results are reported in Table 2, based on the following specification:

$$EV_{pt}^4 = \beta \cdot Post2012_{t-1} + \gamma \cdot X_{p,t-1} + \delta_{province} + \epsilon_{pt}, \tag{4}$$

where EV_{pt} denotes the yearly average of the eigenvector components associated with the dominant eigenvalue for province p in year t, and the dependent variable is expressed in fourth power to preserve consistency with the IPR-based divergence measure. $Post2012$ is a binary indicator for the post-2012 period, capturing the post-sovereign crisis phase. $X_{p,t-1}$ represents the vector of lagged provincial controls—including unemployment, value added per capita, exports, financial risk, and the number of registered firms—while $\delta_{province}$ denotes province fixed effects.

All explanatory variables are lagged by one period to mitigate potential simultaneity concerns and to allow provincial economic conditions to precede observed changes in credit divergence. The inclusion of province fixed effects ensures that identification relies on within-province variation over time, abstracting from time-invariant structural differences across territories.

We find that, after 2012, mortgage credit exhibits a modest increase in synchronization relative to the pre-crisis period (see Table 2). By contrast, unsecured credit growth becomes significantly less synchronized, pointing to greater provincial divergence in this segment following the sovereign debt crisis.

[13]Raising the eigenvector components to the fourth power also addresses the sign indeterminacy inherent in their definition.

[14]Export volumes proxy for international trade activity, as import data are unavailable after 2012. Financial risk is measured as the ratio of non-performing assets to performing assets. The number of firms refers to the stock recorded on December 31 of each year.

The control variables provide additional evidence on the structural drivers of credit dispersion. A higher unemployment rate is positively associated with subsequent mortgage divergence, indicating that weaker local labour market conditions amplify heterogeneity in mortgage dynamics across provinces. For unsecured loans, value added per capita is negatively related to synchronization, implying that provinces with lower economic output per capita tend to display stronger common dynamics in unsecured credit growth.

This pattern is consistent with a *synchronizing effect of crises*, whereby adverse economic conditions generate more homogeneous credit contractions across territories. Importantly, synchronization should not be equated with credit expansion. Rather, it reflects the degree of alignment in credit fluctuations across provinces, irrespective of whether these fluctuations are positive or negative.

Table 2: Determinants of divergence

	(1) All	(2) Mortgages	(3) Unsecured
Post 2012	-0.201*	-0.180*	0.306***
	(0.0806)	(0.0769)	(0.0854)
Value added (p.c.)	0.140	0.159	-0.421***
	(0.126)	(0.113)	(0.123)
Export	0.000808	-0.0605	-0.0944
	(0.0895)	(0.0786)	(0.137)
Unemployment rate	0.130*	0.146*	0.00910
	(0.0622)	(0.0575)	(0.0676)
Financial risk	0.0411	0.0276	-0.0167
	(0.0270)	(0.0235)	(0.0276)
N. Registered firms	0.157	0.0527	-0.354
	(0.153)	(0.109)	(0.390)
Observations	1548	1548	1548
R^2	0.620	0.657	0.340
R^2 adj.	0.591	0.630	0.290

Standardized beta coefficients; Clustered standard errors in parentheses; Variables winsorised at 0.05. Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimating Eq. 4 separately by credit component provides additional insights into the evolution of syn-

Table 3: Determinants of divergence by type of counterpart

	(1) Mortgages	(2) Mortgages (households)	(3) Mortgages (companies)	(4) Unsecured	(5) Unsecured (companies)
Post 2012	-0.180*	-0.0149	-0.171*	0.306***	0.189*
	(0.0769)	(0.0662)	(0.0844)	(0.0854)	(0.0815)
Value added (p.c.)	0.159	-0.0763	-0.777***	-0.421***	-0.0140
	(0.113)	(0.101)	(0.186)	(0.123)	(0.146)
Export	-0.0605	0.0740	-0.355*	-0.0944	0.00970
	(0.0786)	(0.0796)	(0.135)	(0.137)	(0.150)
Unemployment rate	0.146*	0.0153	0.0367	0.00910	0.0604
	(0.0575)	(0.0548)	(0.0643)	(0.0676)	(0.0678)
Financial risk	0.0276	0.0139	0.0381	-0.0167	-0.0204
	(0.0235)	(0.0241)	(0.0243)	(0.0276)	(0.0263)
N. Registered firms	0.0527	0.0173	-0.954***	-0.354	-0.354*
	(0.109)	(0.176)	(0.178)	(0.390)	(0.149)
Observations	1548	1548	1548	1548	1548
R^2	0.657	0.748	0.331	0.340	0.259
R^2 adj.	0.630	0.729	0.281	0.290	0.203

Standardized beta coefficients; Clustered standard errors in parentheses; Variables winsorised at 0.05.
Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

chronization and divergence. The post-2012 increase in mortgage synchronization is confirmed; however, this effect is largely driven by mortgages to companies rather than to households. As previously noted, the volume of corporate mortgages has declined steadily since 2012 (Fig. 1c). The regression results suggest that the observed rise in synchronization reflects a relatively uniform contraction in mortgage lending to firms across provinces (see Table 3).

By contrast, unsecured loans to companies display a marked increase in divergence after 2012. This indicates that, although corporate mortgage lending contracted in a broadly homogeneous manner, the expansion and contraction phases of unsecured corporate credit followed more differentiated provincial trajectories. The resulting pattern points to growing fragmentation in this segment of the credit market, with firm-level unsecured lending evolving unevenly across territories.

Finally, the regression results indicate that loan maturity does not constitute a primary source of territorial differentiation in credit dynamics. Although the post-2012 binary variable is statistically significant in both short- and long-term specifications (Table 4), its sign differs across credit types.

Specifically, the coefficient is negative for mortgages and positive for unsecured loans. Given that the dependent variable captures provincial divergence, this implies that, after 2012, mortgage lending became more synchronized across provinces, whereas unsecured credit growth exhibited increased dispersion. These results further confirm that the key dimension of territorial fragmentation lies in the type of credit and borrower rather than in loan duration.

Table 4: Determinants of divergence by duration

	(1) Mortgages	(2) Mortgages (short-term)	(3) Mortgages (long-term)	(4) Unsecured	(5) Unsecured (short-term)	(6) Unsecured (long-term)
Post 2012	-0.180*	-0.156*	-0.111^{+}	0.306***	0.321**	0.253**
	(0.0769)	(0.0761)	(0.0638)	(0.0854)	(0.109)	(0.0788)
Value added (p.c.)	0.159	0.138	0.0606	-0.421***	-0.336^{+}	-0.109
	(0.113)	(0.104)	(0.107)	(0.123)	(0.170)	(0.120)
Export	-0.0605	-0.0274	-0.0165	-0.0944	-0.0781	-0.300*
	(0.0786)	(0.0906)	(0.0901)	(0.137)	(0.146)	(0.140)
Unemployment rate	0.146*	0.111^{+}	0.0552	0.00910	0.0748	-0.135^{+}
	(0.0575)	(0.0640)	(0.0473)	(0.0676)	(0.0717)	(0.0728)
Financial risk	0.0276	0.0332	0.0183	-0.0167	-0.0163	-0.0383
	(0.0235)	(0.0256)	(0.0223)	(0.0276)	(0.0283)	(0.0267)
N. Registered firms	0.0527	0.151	-0.111	-0.354	0.453	-0.164
	(0.109)	(0.121)	(0.0944)	(0.390)	(0.355)	(0.353)
Observations	1548	1548	1548	1548	1548	1548
R^2	0.657	0.616	0.705	0.340	0.314	0.140
R^2 adj.	0.630	0.587	0.682	0.290	0.263	0.0750

Standardized beta coefficients; Clustered standard errors in parentheses; Variables winsorised at 0.05.
Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.1 Robustness checks

Several robustness exercises corroborate the main findings. First, Eq. 4 is re-estimated using a random effects specification. The results, reported in Appendix D.1, confirm the significance of the post-2012 effect under this alternative framework. Nevertheless, both the Hausman test and the over-identification test support the fixed effects specification as the preferred model (see Appendix D.2), indicating that unobserved province-specific heterogeneity is correlated with the regressors.

Second, the impact of the sovereign debt crisis appears more pronounced when the dependent variable is defined using the median of the eigenvector component distribution rather than the mean (Figure 13). Table D.4 reports the estimates from a quantile regression centred at the median. The post-2012 effect on provincial divergence is stronger at the median than in the mean regression, suggesting that the crisis-induced fragmentation is not driven solely by extreme provinces but affects the central mass of the distribution.

To assess the appropriateness of the post-2012 binary specification, one may question whether changes in credit divergence were already triggered by the 2008 Great Financial Crisis. To address this concern, we re-estimate the model replacing the post-2012 indicator with a post-2008 dummy variable. As reported in Table D.5, the post-2008 coefficient is not statistically significant once province-specific controls are included. This evidence indicates that the structural shift in credit synchronization is primarily associated with the sovereign debt crisis rather than with the initial shock of 2008.

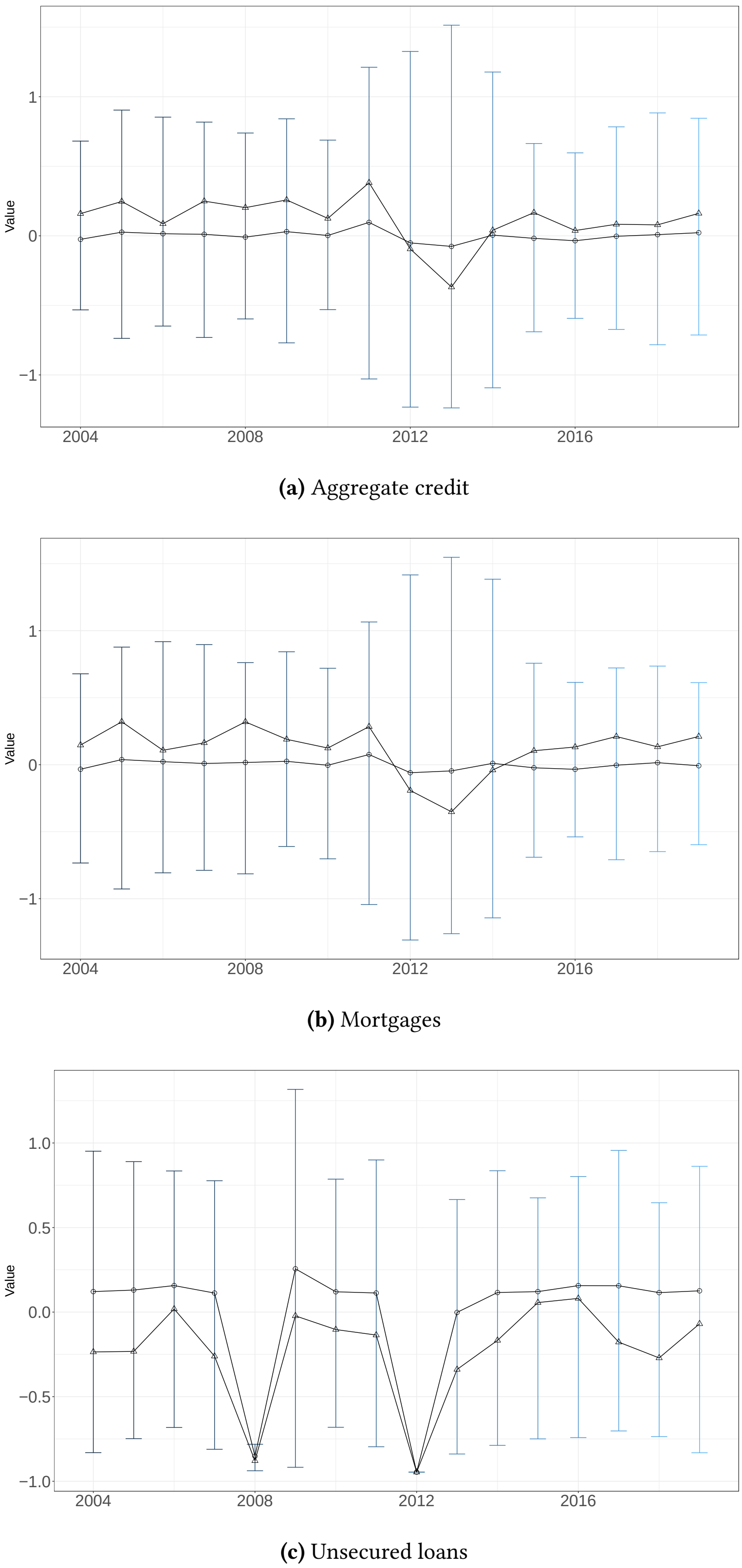
Regarding sample composition, three Italian provinces—Barletta-Andria-Trani, Fermo, and Monza e della Brianza—were established only in 2004, with data availability starting in 2010. Because these provinces are observed mainly in the post-2012 period, their inclusion could potentially bias the estimated post-crisis effect. We therefore re-estimate the model excluding them. The results, reported in Table D.6, confirm that the main conclusions remain unchanged.

7 Discussion

Our analysis of credit synchronization and divergence in Italy yields three main stylized facts. First, the level of aggregation is crucial. Although total credit growth appears highly synchronized, this pattern is primarily driven by household mortgages, while corporate mortgages and unsecured lending display substantial territorial divergence. The apparent national co-movement thus masks important heterogeneity across credit segments and borrower types.

Second, neither the temporal nor the spatial configuration of synchronization follows a stable geographical structure. Provinces move in and out of synchronization over time, preventing the consolidation of persistent spatial clusters such as a traditional North–South divide. This suggests that provincial credit dynamics cannot be fully explained by broad macro-regional classifications and are instead shaped by more localized economic and financial conditions.

Third, the dispersion of unsecured credit growth has increased markedly since 2012. Local economic fundamentals play a significant role in explaining this pattern. Higher unemployment is associated with greater provincial divergence in credit dynamics, whereas higher value added per capita is linked to stronger synchronization. These findings indicate that macroeconomic and financial conditions at the provincial level



(a) Aggregate credit

(b) Mortgages

(c) Unsecured loans

Figure 13: Distribution of the eigenvector components (standardized fourth-power)

materially influence the degree of alignment with the national credit cycle, reinforcing the view that credit market fragmentation operates through territorially differentiated mechanisms.

The policy implications of our findings are twofold. First, from a European perspective, the results point to a potential tension in crisis management. Although unconventional monetary policies have been effective in containing financial stress (Altavilla et al., 2019, 2020), our evidence indicates that the post-crisis period coincided with an increase in within-country credit dispersion in Italy. This suggests that, while monetary policy can stabilize aggregate credit conditions, its transmission may generate differentiated effects across local economies, potentially reinforcing territorial heterogeneity over time.

Second, provincial economic characteristics are closely associated with credit growth dispersion (Table 2). This indicates that heterogeneity arises not only from asymmetric local shocks but also from differences in how provinces respond to common monetary conditions. In particular, episodes of financial tension in sovereign bond markets appear to operate as asymmetric shocks, altering the transmission of monetary policy and contributing to divergent credit dynamics across provinces.

Promoting a more symmetric transmission of monetary policy therefore requires European authorities to account for within-country territorial effects. In this context, macroprudential policies can play a complementary role in mitigating regional imbalances. By adjusting capital, liquidity, and risk-based requirements at the national or sectoral level, macroprudential instruments can help smooth the local transmission of monetary policy and reduce the risk that common interventions translate into uneven credit outcomes.[15]

8 Concluding remarks

This paper examines credit synchronization across Italian provinces at a high level of geographical granularity. Synchronization within regions at different spatial aggregation levels is central to the homogeneous transmission of monetary policy, as asymmetric local dynamics may otherwise generate uneven effects. To measure and characterize synchronization and divergence, we apply Random Matrix Theory (RMT) to a confidential dataset from the Centrale del Rischio Finanziario (CRIF). The RMT framework enables us to distinguish economically meaningful co-movements in credit growth from spurious correlations. RMT-significant eigenvalues identify common factors, while eigenvector components capture the extent to which individual provinces align with these dynamics. This approach allows us to quantify and map credit synchronization and divergence across Italian provinces and to analyze their structural features.

The results highlight three main patterns. First, aggregate credit growth appears homogeneous, but this synchronization is largely driven by mortgages. Unsecured lending displays substantially higher divergence, and credit to firms is consistently more heterogeneous than credit to households. The evidence therefore

[15]For an overview of the macroprudential policy framework in Europe see Bank for International Settlements (2010); Financial Stability Board (2011), among others.

underscores the importance of disaggregated analysis: synchronization and divergence operate unevenly across credit segments and borrower types.

Second, the analysis of regional contributions to common credit dynamics does not reveal persistent macro-regional clusters. No stable North–South asymmetry emerges. Instead, divergence is dispersed across italian provinces and varies over time, indicating that credit fragmentation does not neatly align with traditional geographical classifications.

Third, the post-2012 period is associated with a marked increase in credit dispersion, particularly in unsecured lending. Provincial economic conditions are systematically related to this pattern. Higher unemployment is associated with greater divergence in mortgage dynamics, while lower value added per capita is linked to stronger common movements in unsecured credit, consistent with crisis-induced synchronization during downturns.

Several avenues for future research follow from these findings. Extending the analysis to more recent data, including the Covid-19 period, would allow for a fuller assessment of evolving credit dynamics. Further work could also move beyond measurement to examine the causal mechanisms underpinning credit dispersion. Finally, a comparative analysis across Euro Area countries would provide a broader perspective on within-country financial fragmentation and its policy relevance.

The results have implications for Euro Area governance. Within-country credit divergence may weaken the uniform transmission of monetary policy and highlights the importance of complementary macroprudential and structural policies. Instruments such as capital buffers, liquidity requirements, and sector-specific measures can be calibrated to mitigate localized imbalances, while structural policies addressing regional disparities in labour markets and economic capacity may reduce the persistence of financial fragmentation.

By proposing a framework to measure credit synchronization and divergence at a fine territorial scale, this study contributes to the literature on regional financial integration and provides a tool for assessing the spatial transmission of monetary and macroprudential policies.

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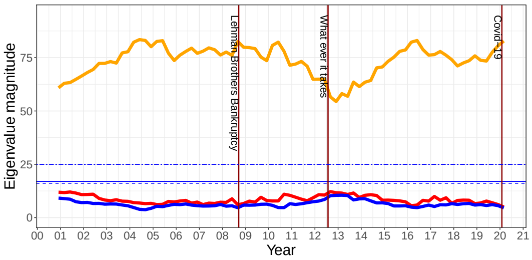
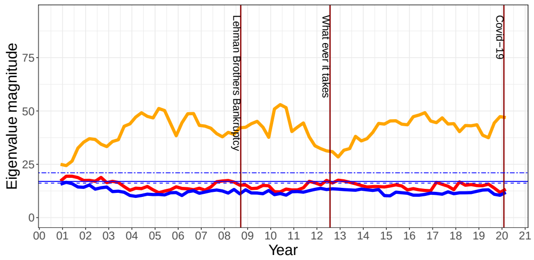
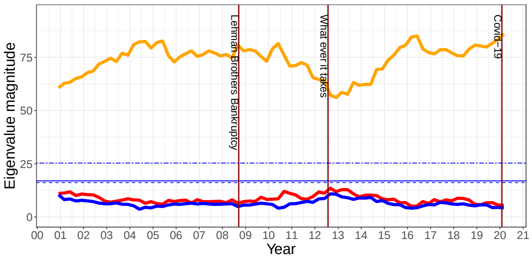
Appendix A. Complete RMT results



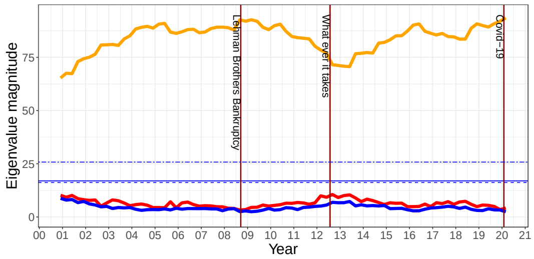
(a) Total credit



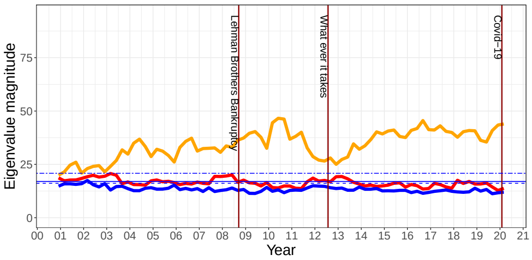
(b) Unsecured loans



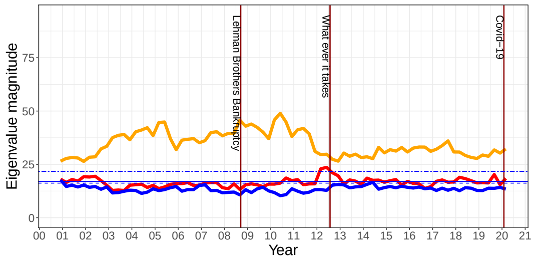
(c) Mortgages



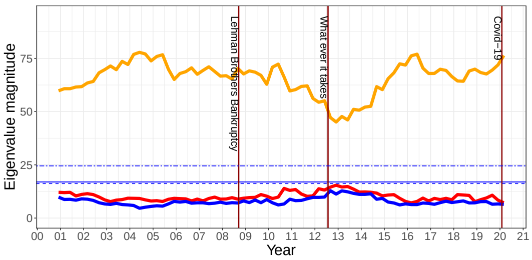
(d) Mortgages to households



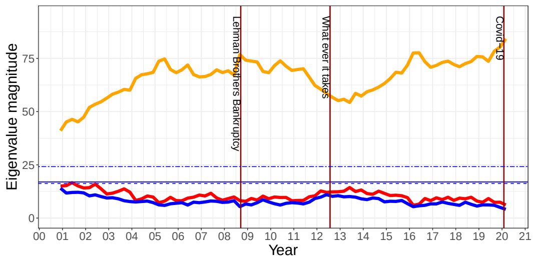
(e) Unsecured loans to company



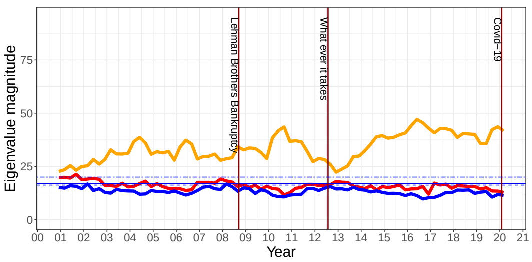
(f) Mortgages to company



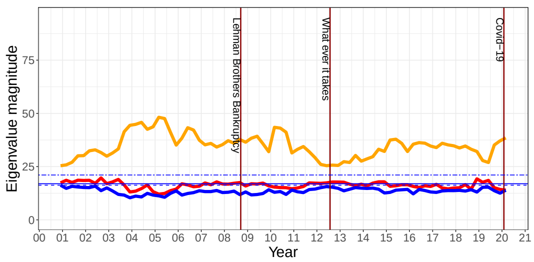
(g) Mortgages, maturity below 20 years



(h) Mortgages, maturity above 20 years

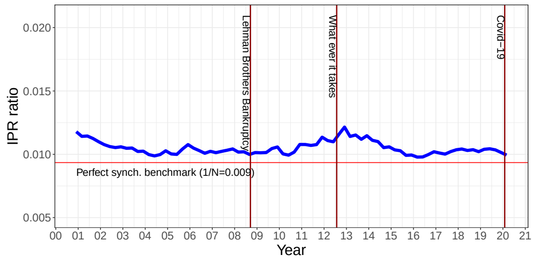


(i) Unsecured loans, maturity below 4 years

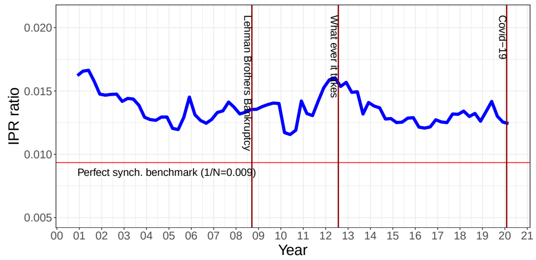


(j) Unsecured loans, maturity above 4 years

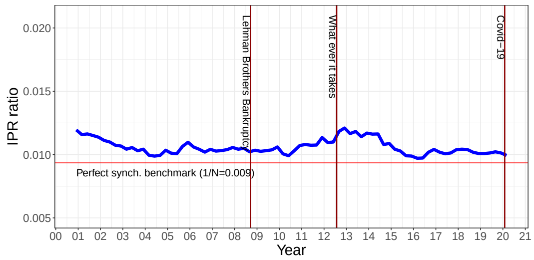
Figure A.1: Eigenvectors of RMT analysis



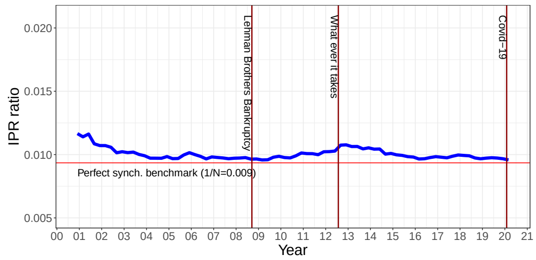
(a) Total credit



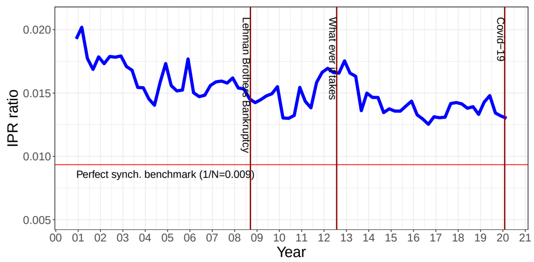
(b) Unsecured loans



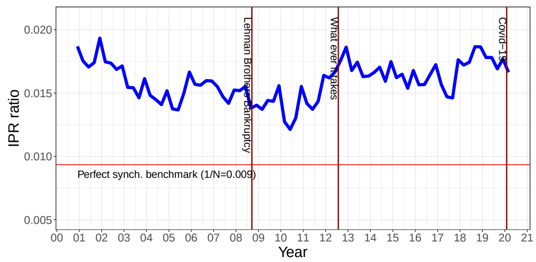
(c) Mortgages



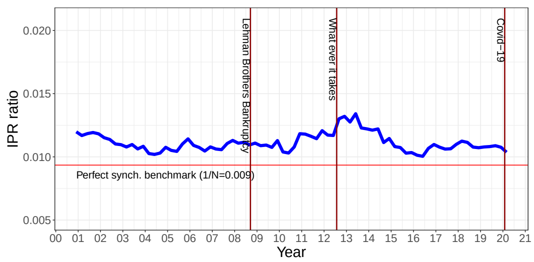
(d) Mortgages to households



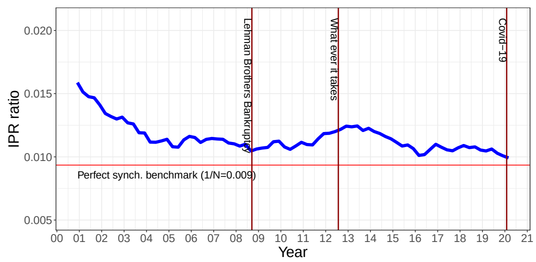
(e) Unsecured loans to company



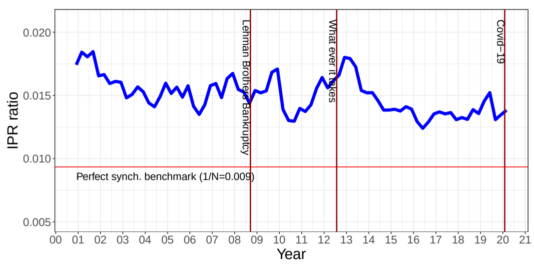
(f) Mortgages to company



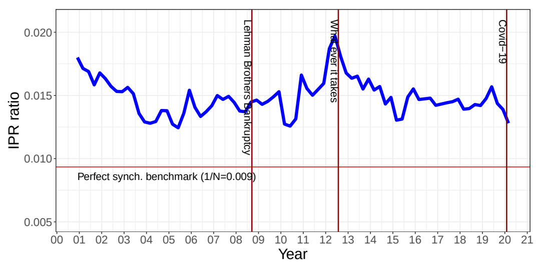
(g) Mortgages, maturity below 20 years



(h) Mortgages, maturity above 20 years

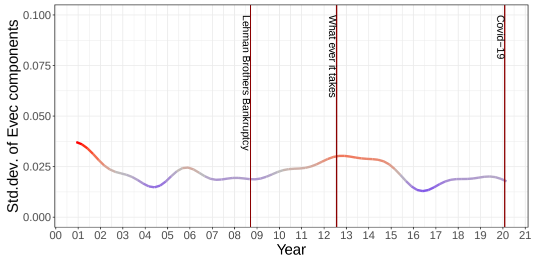


(i) Unsecured loans, maturity below 4 years

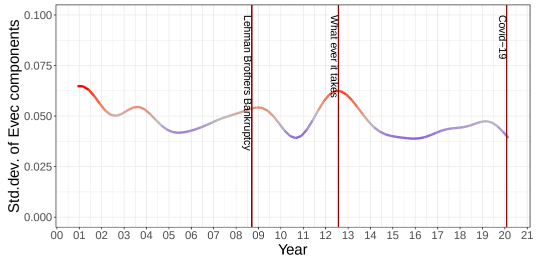


(j) Unsecured loans, maturity above 4 years

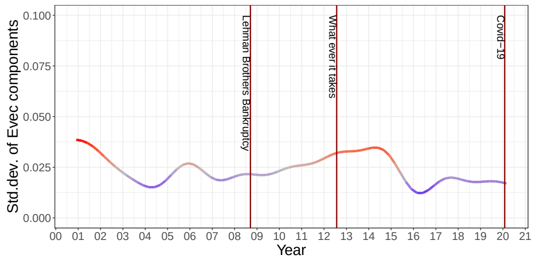
Figure A.2: IPR



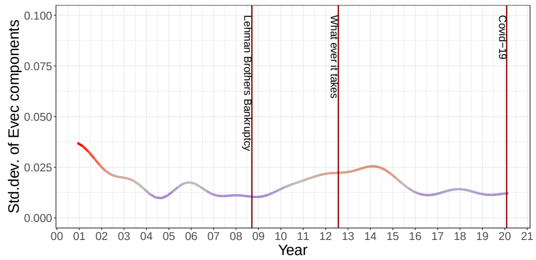
(a) Total credit



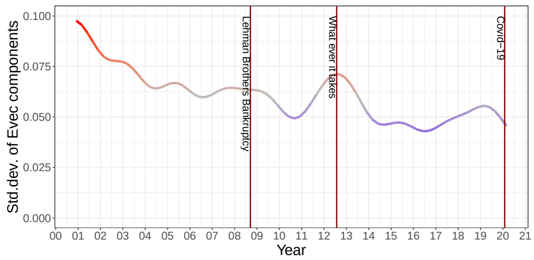
(b) Unsecured loans



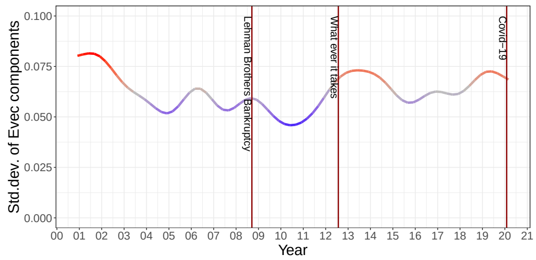
(c) Mortgages



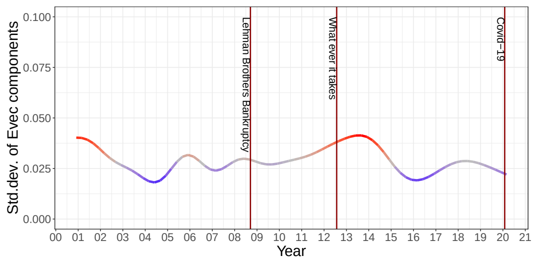
(d) Mortgages to households



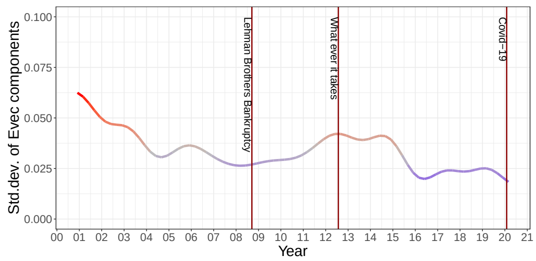
(e) Unsecured loans to company



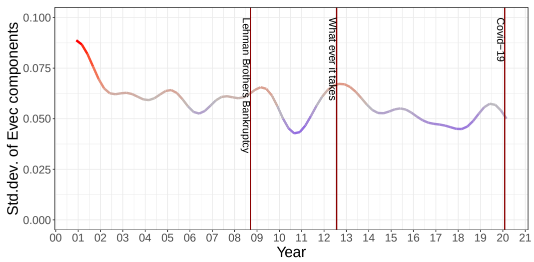
(f) Mortgages to company



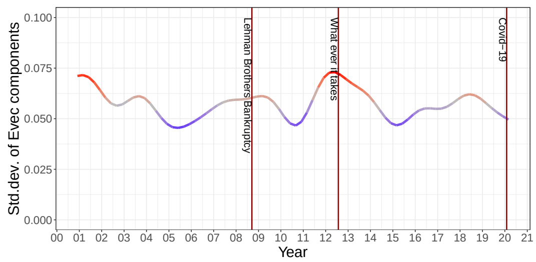
(g) Mortgages, maturity below 20 years



(h) Mortgages, maturity above 20 years



(i) Unsecured loans, maturity below 4 years



(j) Unsecured loans, maturity above 4 years

Figure A.3: Standard deviation of eigenvector components

Appendix B. Additional null models

B.1 Heavy tails

The presence of outliers in the filtered dataset raises the question of whether a Gaussian null model provides an appropriate benchmark for identifying significant components. Biroli et al. (2007) extend the RMT framework to the case in which the underlying distribution of observations exhibits heavy tails.

To account for potential heavy-tailed behaviour, the Marčenko-Pastur law is adjusted as follows. Let S denote the maximum value of the time series within a given rolling window of X observations. Assuming that X follows a heavy-tailed distribution, the adjusted RMT upper bound for the eigenvalues λ_{max} is defined as:

$$\lambda_{max} = \begin{cases} \sigma^2 \left(1 + \sqrt{\frac{1}{Q}}\right)^2, & \text{if } S \leq (NT)^{\frac{1}{4}} \\ (\frac{1}{Q} + \frac{S^2}{T})(1 + \frac{T}{S^2}), & \text{if } S > (NT)^{\frac{1}{4}} \end{cases} \tag{B.1}$$

where $Q = T/N$ and $\sigma^2 = 1$ given that the series are standardized.

Figure B.1 reports the results of this robustness exercise. The adjusted Marčenko-Pastur threshold differs slightly from the Gaussian benchmark only in the initial years of the sample. The magnitude of the adjustment remains limited and does not alter the identification of significant components.

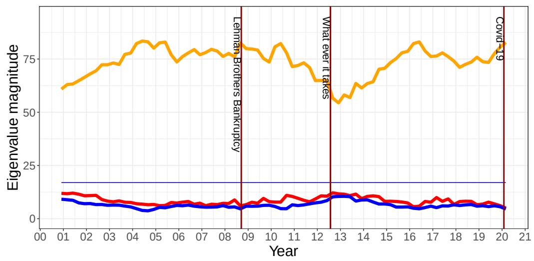
B.2 Rotational random shuffling

Previous studies applying random matrix theory show that autocorrelation in time series can induce fat tails in the empirical eigenvalue distribution (see Aoyama et al., 2017). In such cases, additional principal components may appear significant relative to the Marčenko-Pastur upper bound, even if they do not reflect genuine cross-sectional co-movement.

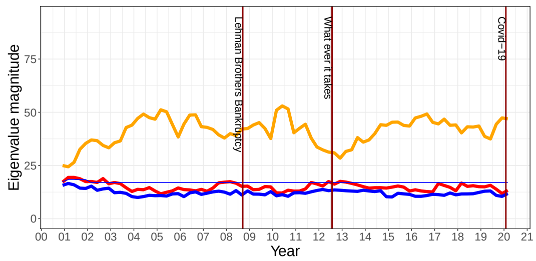
To address this issue, we implement a rotational random shuffling (RRS) Monte Carlo procedure as proposed by Aoyama et al. (2017) and Iyetomi et al. (2011). Formally, we apply the following transformation:

$$x_n(t_i) \rightarrow \begin{cases} x_n(t_{T-|i-\tau|}) & \text{if } i \leq \tau \\ x_n(t_{|i-\tau|}) & \text{if } i > \tau \end{cases} \tag{B.2}$$

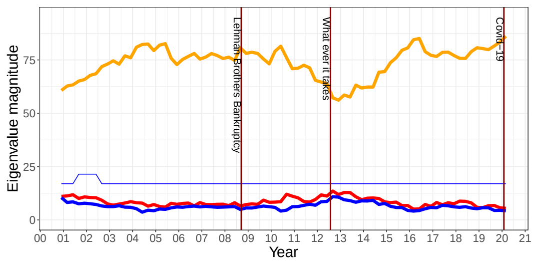
where $x_n(t_i)$ denotes the observation of series n at time t_i, with $i \in [1, T]$, and τ is a random integer drawn from $[1, T]$. The procedure splits each series at τ and rotates the two segments. This operation is equivalent to shifting the series by a random number of observations, with values exceeding the sample length reintroduced at the beginning. Because each series is rotated by a different random shift, cross-correlations across series



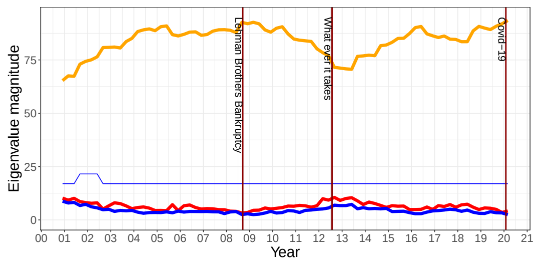
(a) All loans



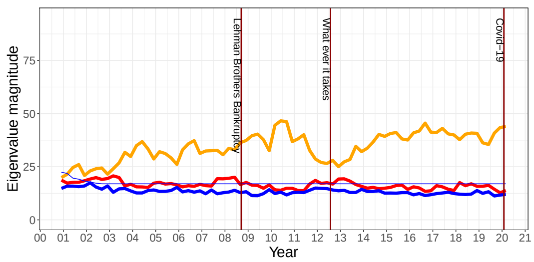
(b) Unsecured loans



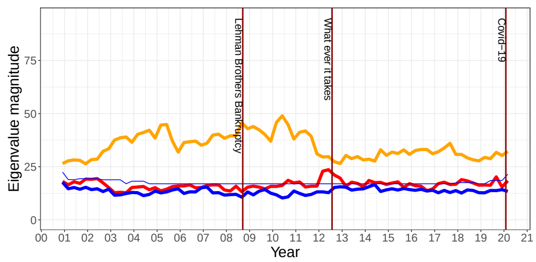
(c) Mortgages



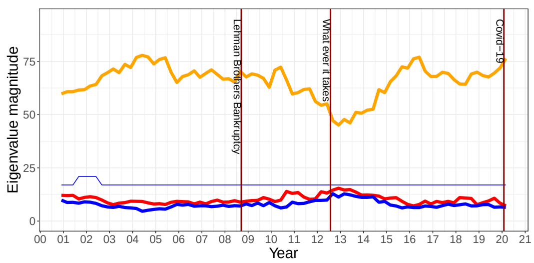
(d) Mortgages to households



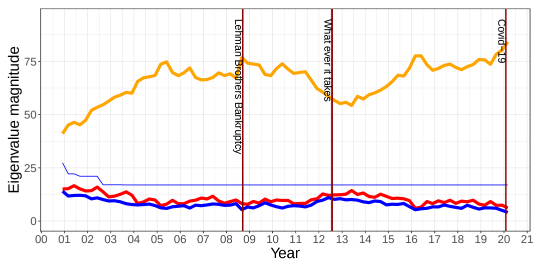
(e) Unsecured loans to company



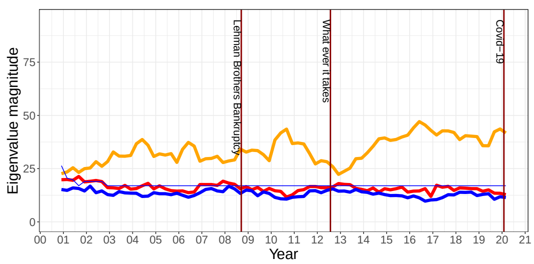
(f) Mortgages to company



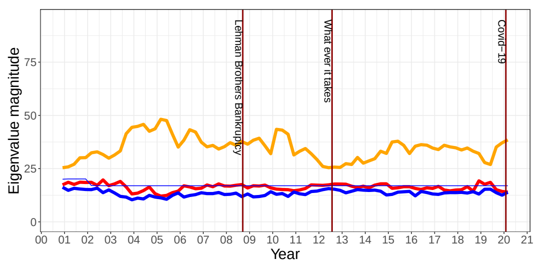
(g) Mortgages, maturity below 20 years



(h) Mortgages, maturity above 20 years



(i) Unsecured loans, maturity below 4 years



(j) Unsecured loans, maturity above 4 years

Figure B.1: Power law robustness check are disrupted while their internal autocorrelation structure is preserved.[16]

We perform multiple Monte Carlo iterations of this procedure within each rolling window. For each window, we compute the average of the maximum eigenvalues obtained from the simulated series, together with the associated confidence intervals. The average maximum eigenvalue provides a new empirical upper bound for testing the significance of the observed eigenvalues. Eigenvalues exceeding the RRS bound capture variance that cannot be attributed solely to autocorrelation and therefore reflect genuine cross-sectional co-movement. By construction, this bound is more stringent than the standard Marčenko-Pastur threshold.

The resulting upper bound corresponds to the thin dotted lines in Figure A.1. The main findings remain robust. The largest component remains significant in all specifications. The RRS adjustment primarily affects the second component, whose significance is reduced in some windows. Nonetheless, the second eigenvalue remains above the RRS bound for unsecured loans to companies and mortgages to companies (Fig. A.1e-f), confirming the conclusions regarding synchronization and divergence across credit segments.

[16]For example, consider a time series of $T = 130$ observations with $\tau = 54$. Observations 55 to 130 are reassigned to positions $|55-54| = 1$ through $|130-54| = 76$, while observations 1 to 54 are shifted to positions $130-|1-54| = 77$ through $130-|54-54| = 130$.

Appendix C. Summary statistics

Table C.1: Summary statistics for standardized variables

	Mean	SD	Count	Min	p25	p50	p75	Max
Eigenvector components relative to the largest eigenvalue								
Aggregate credit	4.52e-09	1	1712	-2.447884	-.5124695	.316462	.7751067	1.174323
Mortgages	-1.82e-09	1	1712	-2.428607	-.5248383	.3340748	.771973	1.141194
Unsecured credit	2.25e-09	1	1712	-2.004341	-.6721537	.1898189	.8463044	1.349161
Mortgages (to households)	-3.06e-09	1	1712	-2.634462	-.4108566	.3692449	.7019634	1.100971
Mortgages (to companies)	-3.14e-11	1	1712	-1.808788	-.8027451	.0796495	.8026464	1.586828
Unsecured credit (to companies)	2.27e-09	1	1712	-1.837605	-.7729149	.0383055	.8501824	1.539966
Mortgages (short-term)	1.96e-09	1	1712	-2.283545	-.604802	.2667084	.7997454	1.220995
Mortgages (long-term)	7.51e-09	1	1712	-2.352783	-.4840601	.3365195	.789941	1.102179
Unsecured credit (short-term)	-2.29e-09	1	1712	-1.929577	-.7242874	.1146359	.8248149	1.484715
Unsecured credit (loan-term)	1.92e-10	1	1712	-1.714547	-.7361546	-.0078353	.7388619	1.740863
ISTAT (Provincial data)								
Value added (p.c.)	3.88e-11	1	1696	-1.781725	-.9121093	.0129928	.6526426	4.621082
Export	2.76e-10	1	1680	-.6920108	-.5788584	-.3231079	.1514823	8.231148
Unemployment rate	-1.07e-09	1	1681	-1.442812	-.7677965	-.2582977	.5417914	3.998003
Finanacial risk index	3.80e-10	1	1594	-1.393063	-.7100241	-.2051863	.4625113	8.868494
Number of registered firms	-9.75e-10	1	1672	-.7004596	-.4605519	-.2837126	.0627184	7.054637

Appendix D. Robustness checks

D.1 Random effects

Table D.1: Determinants of divergence, random effects

	(1) All	(2) All	(3) Mortgages	(4) Mortgages	(5) Unsecured	(6) Unsecured
Post 2012	-0.0287	-0.183*	-0.0279	-0.177*	0.227***	0.269**
	(0.0423)	(0.0747)	(0.0384)	(0.0711)	(0.0481)	(0.0828)
Value added (p.c.)		0.159^{+}		0.208**		-0.107^{+}
		(0.0854)		(0.0802)		(0.0640)
Export		0.101		0.0559		0.222*
		(0.0911)		(0.0833)		(0.0885)
Unemployment rate		0.0857		0.109*		-0.0724
		(0.0575)		(0.0531)		(0.0631)
Financial risk		0.0407		0.0281		-0.00385
		(0.0258)		(0.0224)		(0.0259)
N. Registered firms		0.299**		0.288**		0.272***
		(0.0994)		(0.107)		(0.0508)
Observations	1605	1548	1605	1548	1605	1548
R^2 overall	0.000204	0.202	0.000195	0.195	0.0128	0.191

Standardized beta coefficients; Clustered standard errors in parentheses; Variables winsorised at 0.05. Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.2 Statistical tests

Table D.2 reports the p-values of the Hausman test for the main specifications presented in columns 2, 4, and 6 of Table 2. In all three cases, the null hypothesis of no systematic difference between fixed and random effects estimators is rejected, indicating that the fixed effects specification is preferred.

In addition, we perform the overidentification test described in Arellano (1993) and (Wooldridge, 2010, pp. 290–91). This procedure re-estimates the random effects model augmented with the original regressors

Table D.2: Hausman test

Hausman test	p-value
Aggregate credit	0.0048
Mortgages	0.0015
Unsecured credit	0.0001

Overidentification	p-value
Aggregate credit	0.0011
Mortgages	0.0000
Unsecured credit	0.0006

Table D.3: Additional tests

F test for joint significance of time fixed effects	
Prob > F	0.4897

Modified Wald test for groupwise heteroskedasticity	
Prob > chi2	0.0000

expressed in deviations-from-mean form. As discussed in Schaffer and Stillman (2006), the fixed effects estimator relies on the orthogonality condition that the regressors are uncorrelated with the idiosyncratic error term, whereas the random effects estimator additionally requires orthogonality between the regressors and the group-specific error component (the random effect). These additional restrictions can be tested as overidentifying conditions. Under conditional homoskedasticity, the resulting test statistic is asymptotically equivalent to the standard Hausman test.

Table D.2 presents the p-values for aggregate credit, mortgages, and unsecured loans. Consistent with the Hausman results, the null hypothesis in favour of the random effects model is rejected in all cases.

Table D.3 reports the results of two additional diagnostic tests. First, we assess the joint significance of year fixed effects by testing the null hypothesis that all time dummies are equal to zero. The null hypothesis cannot be rejected, indicating that year fixed effects are not jointly significant in the baseline specification.

Second, we test for heteroskedasticity using a Wald test adapted to fixed effects panel models. The null hypothesis of homoskedasticity is rejected. Accordingly, all regressions are estimated with clustered standard errors to account for heteroskedasticity.

D.3 Quantile regression

Table D.4: Quantile regression (median)

	(1) All	(2) All	(3) Mortgages	(4) Mortgages	(5) Unsecured	(6) Unsecured
Post 2012	-0.00129	-0.211***	-0.0735***	-0.313***	0.191***	0.275***
	(0.0159)	(0.0323)	(0.0184)	(0.0338)	(0.0108)	(0.0215)
Value added (p.c.)		0.270***		0.203***		-0.404***
		(0.0469)		(0.0492)		(0.0480)
Export		-0.0490		-0.0188		-0.121
		(0.0353)		(0.0533)		(0.0756)
Unemployment rate		0.113***		0.201***		-0.0415
		(0.0242)		(0.0335)		(0.0259)
Financial risk		0.0575***		0.0426**		0.000263
		(0.0137)		(0.0132)		(0.00971)
N. Registered firms		0.153		-0.0158		-0.453
		(0.119)		(0.0660)		(0.385)
Observations	1605	1548	1605	1548	1605	1548

Standardized beta coefficients; Robust errors in parentheses; Variables winsorised at 0.05. Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.4 Other robustness checks

Table D.5: Determinants of divergence, control for post-2008 dummy

	(1) All	(2) All	(3) Mortgages	(4) Mortgages	(5) Unsecured	(6) Unsecured
Post 2008	-0.0123	-0.0401	-0.0260	-0.0617	0.143**	0.0971
	(0.0431)	(0.0544)	(0.0373)	(0.0481)	(0.0489)	(0.0629)
Value added (p.c.)		0.0461		0.0884		-0.298*
		(0.120)		(0.105)		(0.126)
Export		-0.0578		-0.109		-0.0111
		(0.0928)		(0.0830)		(0.145)
Unemployment ratio		0.0191		0.0536		0.169***
		(0.0470)		(0.0444)		(0.0461)
Financial Risk		0.0274		0.0188		-0.000787
		(0.0272)		(0.0220)		(0.0284)
N. Registered firms		0.115		0.0231		-0.301
		(0.164)		(0.116)		(0.401)
Observations	1605	1548	1605	1548	1605	1548
R^2	0.615	0.617	0.656	0.655	0.324	0.334
R^2 adj	0.588	0.588	0.631	0.628	0.276	0.284

Standardized beta coefficients; Robust errors in parentheses; Variables winsorised at 0.05. Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: Determinants of divergence, control for post-2004 provinces

	(1) All	(2) All	(3) Mortgages	(4) Mortgages	(5) Unsecured	(6) Unsecured
Post 2012	-0.0364	-0.210*	-0.0271	-0.185*	0.254***	0.296***
	(0.0441)	(0.0811)	(0.0408)	(0.0777)	(0.0505)	(0.0862)
Value added (p.c.)		0.141		0.163		-0.422***
		(0.126)		(0.113)		(0.123)
Export		0.00433		-0.0568		-0.0991
		(0.0895)		(0.0786)		(0.137)
Unemployment rate		0.138*		0.150*		0.0176
		(0.0623)		(0.0578)		(0.0679)
Financial risk		0.0397		0.0256		-0.0190
		(0.0271)		(0.0235)		(0.0277)
N. Registered firms		0.161		0.0569		-0.350
		(0.154)		(0.109)		(0.387)
Observations	1456	1530	1456	1530	1456	1530
R^2	0.610	0.615	0.650	0.652	0.334	0.337
R^2 adj.	0.580	0.586	0.623	0.626	0.282	0.287

Standardized beta coefficients; Robust errors in parentheses; Variables winsorised at 0.05. Note: the number of observations declines after adding the control variables for *Export* is unavailable for all the years.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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