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REGULAR ARTICLE

Banking diversity and firms' exit: A study on Italian data

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Abstract
With Italian data, this paper investigates the role of institutional banking diversity on firms' exit. Using the Gini–Simpson index, a measure of biodiversity drawn from ecological sciences, we find that banking diversity would have reduced firms' exit rates in the period under investigation (2009–2020), and such a beneficial effect appears sharper for the years of the last financial–sovereign crisis. Both of these findings seem to support the "biodiversity argument" pioneered by Ayadi et al. (2009, 2010), stating that – beyond the merits of any particular bank institutional model – it is indeed the coexistence of a mix of different credit institutions that matters in favouring the financing of the real economy, especially in a scenario characterized by financial turmoil and uncertainty. As a policy recommendation, authorities should promote regulations that, avoiding bias towards a specific bank model, aim to preserve and promote biodiversity in the banking sector.

Keywords Banking diversity · Gini index · Firm exit · Financial crisis · COVID-19 pandemic

JEL Classification G20 · G21 · L60 · R11

1 Introduction

The economic literature has extensively explored the role of banks' characteristics on the financing of firms, a critical factor in explaining their exit from the market. Focusing essentially on the dichotomy between mega-banks (large/multimarket/nonlocal banks) and community credit institutions (small/single-market/local banks) – several contributions have shown that the former, adopting a lending technology based on *hard quantitative information*, tends to serve larger/more transparent firms, while community banks, exploiting a comparative advantage in processing

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soft qualitative information, are more able to fund informationally opaque small businesses via lending relationships (e.g. Stein 2002; Cole et al. 2004; Scott 2004; Berger et al. 2001; 2005a, 2015, 2017; Mkhaiber and Werner 2021). These findings contrast with those of studies providing evidence that community banks no longer have a comparative advantage in serving small enterprises, as technological progress allows large banks to also cater to these firms (e.g. Petersen and Rajan 2002; Frame et al. 2001, 2004; Berger et al. 2005b; Berger and Udell 2006; De Young et al. 2011; Berger et al. 2014).

As the dualism between large and local banks reflects, to a great extent, the heterogeneity that, in terms of legal forms, ownership structures, governance mechanisms and objective functions, characterize the banking sector in many countries – it can be argued that the above research presents counter-arguments and contradictory empirical predictions on the role of institutional bank variety on firms' financing.

A possible explanation for such a mixed picture could rely on considering that the extant contributions mainly focus on the specific strengths and weaknesses of one institutional bank model over another, neglecting the principal insights offered by the "biodiversity" viewpoint. According to this latter, pioneered by Ayadi et al. (2009, 2010), "in many respects it is the mix of different types of institutions that is important (the biodiversity argument) as much (if not more so) than the merits of any particular ownership structure or business model" (Ayadi et al. 2010, p. vi). With specific respect to the issue of firms' financing, a banking landscape populated by a variety of institutional bank types – each one with its business strategies and expertise, lending policies and technologies – might prevent firms from depending on a single bank model, which might not be best suited to all uncertain and unpredictable market circumstances (Llewellyn 2009). Thus, in the absence of a perfect model, the best option is to encourage diversity in the banking sector (Michie and Oughton 2022).

From this perspective, banking diversity is still an under-researched issue (e.g. Kotz and Schäfer 2018), especially concerning how it affects the financing of the real economy and, in particular, the funding of small and medium-sized enterprises (SMEs). This consideration motivates our paper, which aims to contribute to the literature by empirically investigating the impact of institutional diversity in the Italian banking sector on firms' propensity to exit the market.

As the biodiversity argument echoes insights from ecological sciences (e.g. Haldane and May 2011), we resort to a standard "biodiversity" index – the Gini–Simpson index (Simpson 1949) – to measure institutional banking diversity at the local credit markets level, and relate it to the exit rates of manufacturing firms 2009–2020.

The Italian local credit markets – roughly corresponding to the administrative provinces, according to the National Antitrust Authority – represent an ideal setting for our analysis for at least two reasons. First, they are the "natural" reference when considering the issue of bank financing to firms, and these are mainly SMEs (e.g. Petersen and Rajan 1995; Bonaccorsi di Patti and Gobbi 2001). In the Italian case, SMEs account for almost 99.9% of the country's firms. Second, despite the restructuring and consolidation processes – which mainly occurred during the 1990s and early 2000s – have dramatically reduced the number of financial entities, the Italian banking system is still characterized by a variety of institutional types of banks, ranging from large corporations (*banche SpA*) to mutualistic cooperatives (*Banche di Credito Cooperativo* or BCC), from a hybrid type between the previous ones (*Popolari*) to the foreign credit institutions.

To the best of our knowledge, no other studies have quantified the level of institutional banking diversity in the local credit markets of Italy, nor have contributions investigated how it might impact some aspects of firm demography. In this latter respect, our paper also participates in the research on identifying the determinants of firms' exit (e.g. Bottazzi et al. 2011; Honjo and Kato 2019; Cefis et al. 2021, 2022). Further, the time span considered allows us to provide some insights into the role that institutional banking diversity has played during the last two economic crises: the financial–sovereign crisis and the more recent crisis triggered by the COVID-19 pandemic that began in late 2019. Even from this perspective, our paper aims to contribute to the extant research on firms' exit (e.g. Carreira and Teixeira 2016).

According to our results, which are robust to several sensitivity checks, banking diversity in local credit markets negatively impacts firms' exit rates, and such an impact appears stronger for the years of the last financial–sovereign debt crisis. These findings support the biodiversity argument, as they indicate that the coexistence of different institutional bank types can contribute to shaping a favourable environment for firms' financing and resilience. Moreover, our evidence supports the view (e.g. Ayadi et al. 2009) that the last financial–sovereign debt crisis has made even more evident than before the need to preserve and support the institutional pluralism characterizing the European banking sector. Thus, the main policy implication of our analysis can be stated in the words of Ferri (2010, p. 3), claiming that "authorities must be aware that any regulation – e.g. levelling the playing field – should not damage the biodiversity of banking".

The rest of the paper is organized as follows: the next section outlines the research context of our analysis; Section 3 describes how we measure banking diversity; Section 4 is devoted to the econometric model, illustrating the data and the methodology used; Section 5 discusses the results of the empirical analysis and the robustness checks performed; finally, Section 6 provides some concluding remarks, pointing out the main limitations of our study and the issue it leaves for future research.

2 Background literature

As already noted, when referring to bank types, the literature basically discriminates between large/nonlocal banks and small/local credit institutions. In addition to the differences in the organizational structures related to size, this dualism reflects the specificities in banks' institutional form, corporate governance and objective function. Indeed, large banks ordinarily take shape as for-profit corporation institutions (shareholder value banks), whilst small banks are typically community banks (stakeholder value banks) – among which a sizeable portion pursue mutualistic aims, particularly in some European countries (e.g. Coccorese and Shaffer 2021). Besides, institutional and organizational features shape banks' business models and lending technologies: large banks tend to rely on transaction-based technologies, whereas small banks specialize in relationship lending (e.g. Berger and Udell 2006). In the rest of this section – focusing on SMEs that, as mentioned, are the backbone of the Italian (and European) economy – we first briefly review the main literature providing insights on how bank heterogeneity affects firms' financing and then present the argument underlying our empirical analysis.

We move from considering that financial constraints are decisive for SMEs' survival and exit (e.g. Farinha 2005; Ponikvar et al. 2018). Indeed, as these firms are more likely to suffer from severe asymmetric information problems related to their *informational opaqueness* (lacking established track records and adequate collateral), SMEs face more difficulty in obtaining bank credit than larger firms (e.g. Beck and Demirgüç-Kunt 2006; Beck et al. 2013). On this issue, several contributions have shown that a greater presence of community banks in credit markets alleviates SMEs' financial constraints, thus lowering their failure rates (Berger et al. 2015, 2017). The main theoretical argument of these studies is that local banks would have comparative advantages vis-à-vis large financial institutions in lending to SMEs. Indeed, rooted in the territories where they operate, community banks can exploit the knowledge of their local economy and the physical proximity to borrowers to gather *soft information* on them (e.g. Petersen and Rajan 2002). Furthermore, local banks have organizational structures characterised by fewer management layers, which limits managerial diseconomies (e.g. Stein 2002) and facilitates the efficient transmission of qualitative information (e.g. Liberti and Mian 2009). Being advantaged in collecting, verifying and transmitting soft information, local banks may establish close lending relationships with borrowers (e.g. Boot 2000; Elyasiani and Goldberg 2004; Udell 2008). These relationships, in turn, would increase firms' credit availability (e.g. Petersen and Rajan 1994; Cole 1998; Berger and Udell 1995, 2002), reduce interest rates on loans (e.g. D'Auria et al. 1999; Brick and Palia 2007; Bharath et al. 2011), encourage greater borrower discipline (Foglia et al. 1998), enable firms to signal their willingness to abstain from strategic default (Bannier 2007) and reduce small business bankruptcies (Shimizu 2012).

The above predictions, belonging to the so-called *conventional paradigm*, have been questioned by other research, which advocates caution in drawing a conclusive answer to whether a significant market presence of local banks is indispensable for credit availability to SMEs. The theoretical framework of these studies relies on recognising that large banks – while using financial statement lending technology to deal with informationally transparent firms – come with other hard-information-based transaction technologies (such as small business credit scoring, asset-based lending, factoring, fixed-asset lending and leasing) allowing these financial institutions to serve small, opaque firms (e.g. Berger and Udell 2006). This view finds support in several empirical studies, such as Frame et al. (2001, 2004), Clarke et al. (2005), Carter and McNulty (2005), Berger et al. (2005b), De Young et al. (2011), Berger et al. (2014).

Besides, large banks' financing might limit firms' default risk as transaction lending technologies would not suffer from the "dark sides" of lending relationships. Indeed, in a context of tight bank–firm ties, lenders might attempt to monopolise the information they acquire from borrowers to lock them in the relationship (*hold-up* problem) and exploit rents by charging higher loan rates (e.g. Sharpe 1990; Rajan 1992; Degryse and Van Cayseele 2000) – which may result in heavier financial pressure on firms. Further, the so-called *soft-budget constraint* problem can arise in close lending relationships. The latter, enabling easier debt renegotiation *ex-post*, can generate *ex-ante* perverse incentives on borrowers, leading them to behave opportunistically or take excessive risks (e.g. Dewatripont and Maskin 1995; Bolton and Scharfstein 1996).

The discussion so far shows that, on the question of which typology of banks is more suited for SMEs' lending, the extant research presents counter-arguments and contradictory empirical results. An aspect of the reviewed studies, which might be viewed as a possible reason explaining the above-mixed picture, is that they mainly focus on the specific advantages and pitfalls of one institutional bank model over another. Yet, according to the "biodiversity argument" (Ayadi et al. 2009, 2010; Kalmi 2017; Miklaszewska 2017), beyond the merits referable to any particular bank institutional type, is the coexistence of different institutional bank models operating in a market that matters for overall economic efficiency and stability. Stimulated by the advances achieved in the new institutional economics, emphasizing the importance of analysing institutions over their mere description (Schmidt 2018), and by the recognition that the 2007–2009 international financial crisis revealed the shortcomings of neglecting the institutional variety of the financial sector (e.g. Kotz and Schäfer 2018), the biodiversity argument relies on the consideration that, since the economy is a complex system, "we cannot know which [bank business] model will prove to be superior in all possible […] circumstances" (Michie 2011, p. 309). If it is impossible to judge which model is best in all future circumstances, then there is a case for diversity in the banking sector (Michie and Oughton 2022). [1] Indeed, having a mix of institutional banking structures may reduce the overall systemic risk – as, in any potential scenario, some bank types, exploiting their business strategies and portfolio structure, might enjoy more relative stability than others, thus avoiding the bandwagon effect (Llewellyn 2009).[2] Likewise, a banking landscape populated by different types of credit institutions might prevent the financing of the real economy from depending on a single bank model, which might not be best suited to taking on the intermediation function in all uncertain and unpredictable market conditions.

Whilst these considerations are far from allowing us to posit a priori expectations on the specific effects of banking diversity on firms' financing and, thus, their propensity to exit the market, they undoubtedly highlight the paramount relevance of analysing this issue from the biodiversity perspective. In the present paper, we aim to conduct such an analysis by adopting the methodological approach illustrated in the following sections.

[1] In a resolution of 2008, the European Parliament stated that "the diversity of legal models and business objectives of the financial entities in the retail banking sector (banks, savings banks, cooperatives, etc.) is a fundamental asset to the EU's economy which enriches the sector, corresponds to the pluralist structure of the market and helps to increase competition in the internal market".

[2] Similarly, Haldane and May (2011) argue that the probability of the entire financial system collapsing increases as it becomes more and more homogeneous (all banks do the same things). Michie (2011) also highlights that having a more diverse financial service is the major contribution to ensuring the necessary systemic stability. On the same point, see also Goodhart and Wagner (2012) and NEF (2015).

3 Measuring banking diversity

The analysis of diversity in economics echoes insights from bioecological sciences (e.g. Maignan et al. 2003), drawing from them the measurement methods – among which two standards are the Gini–Simpson and the Shannon indexes.

The first one is the complement of the original Simpson index (Simpson 1949):

$$\mathrm{GINI} = 1 - \sum_{i=1}^{K} \left(b_{ipt}\right)^2 \tag{1}$$

where, in the context of our analysis, b_{ipt} is the proportion of branches of bank type i, in province p, at time t. There are four K bank types we consider: the three categories of credit institutions characterizing the Italian banking system – the corporation commercial banks (SpA), the mutual cooperatives banks (*Banche di Credito Cooopèrativo* or BCC) and the *Popolari* cooperatives – and the foreign banks. While the SpA banks consist of for-profit, large financial institutions, the BCCs are generally small, local banks with specific features (regarding ownership structure, corporate governance, statutory requirements, organizational structure and business objectives) that characterize them as mutualistic, not-for-profit credit firms. Finally, the *Popolari* cooperative banks might be considered an intermediate category between the previous two. Indeed, although established in the institutional form of cooperatives, several differences – both at the normative level and in their corporate structures – make *Popolari* more similar to commercial banks than to BCCs.[3] We also include the foreign institutions in consideration of the empirical indications about their role in affecting firms' financing. Even this piece of evidence is, at least, mixed. Indeed, while some studies have shown that foreign banks, using innovative technologies and favouring the introduction of new products, can help SMEs access to credit (e.g. Clarke et al. 2001, 2005), other contributions document that foreign financial institutions "cherry-pick" borrowers, thus undermining overall access to financial services (e.g. Detragiache et al. 2008; Claessens and Van Horen 2014).[4]

From the interpretive point of view (in our setting), the Gini index measures the probability that two branches, drawn randomly from the dataset, belong to different bank types (K). Thus, the index takes its minimum if one bank type only operates in the market, and its value increases as K becomes larger and the degree of equality in the distribution of branches among K increases.

The other standard biodiversity measure is the Shannon (1948) index:

$$\mathrm{SHANNON} = -\sum_{i=1}^{K} b_{ipt} \ln\left(b_{ipt}\right) \tag{2}$$

[3] For a more detailed analysis of the features which strongly distinguish BCC and *Popolari* banks – or, in other words, which make *Popolari* a model closer to that of corporation banks – see, for instance, De Bonis et al. (1994). It is worth noting that, until the early 1990s, another category of banks operated in the Italian credit system: the savings banks. These latter have disappeared because of the profound changes in the national banking regulation that started with the Amato-Carli law of 1990.

[4] For extensive analyses of foreign banks' penetration effects on the development and efficiency of financial systems in the host countries, see Bruno and Hauswald (2013) and Claessens and Van Horen (2014).

With our data, SHANNON gauges the uncertainty in predicting the bank type's identity to which a branch belongs when the latter is taken randomly from the dataset. This uncertainty is low when K is low or most branches belong to the same bank category, increasing as K becomes numerous and the distribution of branches amongst bank types becomes more even.

Since both GINI and SHANNON are affected by the number of bank types and the distribution of their branches,[5] we expect – and indeed find – a high correlation between them (0.986). Therefore – considering that "the ability of two indexes to capture different properties of the data is captured by their correlation coefficient. If the coefficient is close to 1, it implies that the indicators tend to capture very similar features of the data" (Maignan et al. 2003, p. 28) – our empirical analysis relies on the most commonly used Gini–Simpson measure (e.g. Kotz and Schäfer 2018), employing the Shannon index for robustness purposes.

For several reasons, the diversity indexes employed in our analysis should not be viewed as proper measures of interbank competition. Firstly, the structural indicators used in the research to measure credit market concentration, such as the Herfindahl–Hirschman index or the Shannon index (for a review, see Bikker and Haaf 2002), consider the number and the market shares of *individual* banks, while we refer to *types* of banks. Thus, even if our index were proxying for some kind of market competition, the latter would ultimately be among banking species – which is indeed a very close concept to the notion of *diversity* we intend to catch. Secondly, Baum et al. (2020, p. 5) claimed that "despite the assumed link between institutional diversity and competition, we know surprisingly little about the true relationship between those two structural characteristics. High institutional diversity may not necessarily imply that banks lack price-setting power." Finally, as described in the empirical Sub-section 4.2, our econometric model encompasses a direct measure of local credit market structure that – despite its limitations – allows us to account for the competition effect and thus disentangle it from the *diversity* effect.

4 Empirical investigation

4.1 Data

Information to retrieve banking diversity indexes comes from the Italian Banking Association (ABI) and the Bank of Italy. Data on business demography are drawn from the *Movimprese-InfoCamere* dataset, held by the information service consortium of the Italian Chambers of Commerce, providing quarterly and annual data at the provincial-, regional- and industrial-level classification on all active, newly registered and ceased enterprises in Italy since 1995.

As illustrated in the next sub-section, we use data on ceased firms in a year (over the stock of existing active enterprises in the previous one) to obtain firms'

[5] Even though, on a theoretical basis, they are affected differently. On this point, see Maignan et al. (2003).

exit rates. Unfortunately, the *Movimprese* dataset does not provide detailed information on why a firm ceases its activity – whether from failure, liquidation, reorganization, voluntary closures, or because of mergers and acquisitions events. This lack of information precludes the possibility of discriminating between the different exit modes and thus accounting for their distinct meanings – leading us to acknowledge that, in our analysis, exit is not necessarily synonymous with failure or closure (e.g. Parker 2018; Cefis et al. 2022). Nonetheless, we point out two indications according to the empirical evidence on the issue (e.g. Headd 2003; Colantone et al. 2015; Grazzi et al. 2022). First, exit and bankruptcy rates tend to be highly correlated, especially in manufacturing industries. Second, even when the data allow for the retrieval of critical information about the firm status, it is challenging to discriminate between successful and unsuccessful closures in practice.[6]

Although data on business demography are available from 1995, our sample spans from 2009 to 2020. The reason for this is that the classification of economic activities (NACE classification) in the *Movimprese* dataset changed in 2009, passing from NACE Rev.1 (ATECO 2002) to NACE Rev.2 (ATECO 2007), and – since the business demographic information is available at the sectoral two-digit level – we were precluded from obtaining an exact match with the figures until 2008. For the period taken into consideration, we have data on 24 manufacturing sectors and 105 provinces, making our initial sample consisting of a (balanced) panel of 30,240 observations.

Finally, information on provincial and regional features employed as control variables in the econometric model is drawn from the Italian National Institute of Statistics and Eurostat, except for data on deposits and loans provided by the Bank of Italy.

4.2 Model

Our estimating model is the following:

$$\mathrm{EXIT}_{pst} = \alpha + \beta_1 \mathrm{GINI}_{p(t-1)} + \phi \boldsymbol{X}_{(t-1)} + \sum\nolimits_s \gamma_s \mathrm{IND}_s + \sum\nolimits_t \varphi_t T_t + \epsilon_{pst} \tag{3}$$

where the dependent variable is the exit rate (EXIT) of manufacturing firms in province p, industry s, at time t, computed as the ratio of ceased firms over the stock of existing companies at time t–1. On the right-hand side, GINI is our local banking institutional diversity measure. The vector **X** encompasses a set of control variables, measured at the provincial-sectoral (provincial only) or regional-sectoral (regional only) level, according to data availability (see Table 1).[7] It first includes

[6] For instance, Headd (2003) found that 70% of analysed firms were unsuccessful at closure and that the lowest (highest) percentage of firms closing while successful was in the manufacturing industry (services sectors). Grazzi et al. (2022) analysed the dynamics of Italian firms from 2005 to 2014 and documented that the exit rate through M&A is much lower than the "involuntary" exit share.

[7] All the explanatory variables, except the dummy variables, are lagged once to avoid simultaneity bias.

Table 1 Description and summary statistics

		Level of aggregation	Mean	Std. Dev.	Min	Max	Obs.
EXIT [(a)]	Exit rate: ceased firms at time t over the stock of existing firms at time t–1	Provincial-sectoral	4.638	3.558	0	20.0	25,943
GINI	Gini–Simpson index (see Sect. 3)	Provincial	0.431	0.156	0.012	0.714	29,732
HHID	Herfindahl–Hirschman index on deposits	Provincial	0.152	0.062	0.045	0.472	29,732
CREDIT [(a)]	Total bank loans to firms over total deposits	Provincial	120.1	42.56	37.50	302.4	29,684
UNEMPL [(a)]	Unemployment rate	Provincial	10.67	5.48	2.10	31.46	29,684
PARTIC [(a)]	Participation rate	Provincial	64.42	8.27	40.61	76.78	29,684
EMPLOMA [(b)]	Number of employees in manufacturing sectors per thousand inhabitants	Regional-sectoral	28.16	34.41	0	338.6	26,075
FDENS [(b)]	Number of registered firms per 10,000 inhabitants	Provincial-sectoral	102.1	41.13	43.73	384.87	29,732
FSIZE [(b)]	Number of employees in manufacturing firms	Regional-sectoral	12.07	20.44	0	725.7	25,752
JACOB [(b)]	Jacob index: number of sectors (two-digit level) in each province, with more than ten firms	Provincial	19.94	2.24	12	24.0	29,732
VAPC	Per-capita value added	Provincial	22,974	6,241	12,919	50,126	27,251
EXP[(a)]	Export over GDP	Provincial	24.70	23.45	0.06	295.53	27,203
INFRA	Economic and social infrastructure endowment in 2009 (index number, Italy = 100)	Provincial	100.6	28.25	38.90	172.94	29,732
POPDENS [(b)]	Population over provincial surface (in km^2)	Provincial	268.8	378.5	38.34	2652.7	29,732
EDU[(a)]	Share population (25–64) with upper secondary, post-secondary, and tertiary education	Regional	59.21	6.80	43.00	71.80	29,732
DISTRICT	Dummy = 1 for provinces where industrial districts are located		0.526	0.499	0	1	29,732
CITY	Dummy = 1 for the four largest cities in terms of population (Rome, Milan, Naples and Torino)		0.039	0.193	0	1	29,732
ENTRY [(a)]	Entry rate: newly registered firms at time t over the stock of existing firms at time t–1	Provincial-sectoral	2.238	2.585	0	14.29	25,943
CRISIS	Dummy = 1 for the most severe year of the financial–sovereign debt crises in Italy (2011)		0.250	0.433	0	1	29,732

Table 1 (continued)

		Level of aggregation	Mean	Std. Dev.	Min	Max	Obs.
Robustness							
SHANNON	Shannon index (see Sect. 3)	Provincial	0.761	0.252	0.036	1.312	29,732
VAGR[(a)]	Annual growth rate of value added	Provincial	0.898	2.506	-18.27	20.63	24,731
PVSIZE	Provincial size: number of municipalities	Provincial	76.34	55.33	6.0	315.0	29,732
WAGE [(c)]	Average wage in manufacturing sectors	Regional-sectoral	24,356	9524	6818	53,211	24,823
CLOBRA [(a)]	Closed bank branches/Total branches	Provincial	1.904	1.847	0	10.84	29,732
HHIL	Herfindahl–Hirschman index on loans	Provincial	0.159	0.064	0.036	0.519	29,732
RGDPPC [(c)]	Real per-capita gross domestic product	Provincial	26,035	6,949	14,538	55,821	26,735

(a) In percentage; (b) In unit; (c) In euros. To rule out potential outliers, we trim the distribution of EXIT and ENTRY, excluding the observations of the top and bottom one per cent the Herfindahl–Hirschman index on deposits (HHID)[8] and the amount of bank credit provided to firms over deposits (CREDIT) to rule out the possibility that our diversity indexes might indeed capture the degree of banking competition or the availability of bank financing in local credit markets. The vast debate on the role of bank competition on firm financing (e.g. Cetorelli 2001; Agostino et al. 2012) prevents us from anticipating the sign of HHID, whereas we expect a negative effect of CREDIT. The other explicative variables are mainly drawn from the extant literature on business demography focused on the Italian provinces (e.g. Santarelli et al. 2009; Carree et al. 2011; Cainelli et al. 2014; Agostino et al. 2020).

To account for the local labour market conditions, vector **X** includes the unemployment rate (UNEMPL), the participation rate (PARTIC) and the number of employees in manufacturing sectors per thousands of inhabitants (EMPLOMA).[9] Given the different drivers of entrepreneurship, labour market dynamics and the contrasting results obtained in previous works examining firms' exit,[10] it is challenging to posit ex-ante expectations on the signs of these variables.

As proxies for industrial structure, we employ the number of manufacturing firms per 10,000 inhabitants (FDENS), their average size (FSIZE) and the Jacob specialization index (the number of two-digit manufacturing sectors in each province with more than ten firms, JACOB). The net effect of firms' density on exit can be both negative or positive according to competition effects in local markets. Indeed, organizational and spatial proximity to other firms and suppliers may benefit firms (Porter 1998), but competition effects on local resources could increase firms' exit (Cainelli et al. 2014). On the contrary, there is evidence of an inverse relationship between firms' average size and their probability of exiting the market, mainly owing to the greater resource availability of larger firms (see Cefis et al. 2022 for a literature review). Some caution, instead, should be taken when considering the potential role

8 This indicator is obtained as follows: $HHID_p = \Sigma\left(ms_{ip}\right)^2$, where $ms_{ip} = \left(D_{ip}/D_p\right)$ is the market share on deposits for each branch office of bank i in province p, and $D_p = \sum_i D_{ip}$. Since in Italy, like in most other European countries, data at the local banking office level are not publicly available, we follow Carbò Valverde et al. (2003) and draw the variable D_{ip} as, $D_{ip} = D_i * \left(BR_{ip}/BR_i\right)$ where D_i is the amount of deposits as it is provided by the balance sheet of bank i, BR_{ip} is the number of branch offices of bank i in province p and BR_i is the total number of branch offices of bank i. While acknowledging that the Herfindahl–Hirschman index, stemming from the traditional structure–conduct–performance (SCP) paradigm, has been criticized as a measure of competition (for some reviews concerning the banking sector, see Gilbert and Zaretsky 2003; Berger et al. 2004), we notice that Petersen and Rajan (1995) argue that the HHI on deposits "represents a good proxy for competition in loan markets if the empirical investigation involves firms that largely borrow from local markets, that is if credit markets are local for the firms under consideration" (p. 418). Furthermore, using the same criterion, we also compute a Herfindahl–Hirschman index on loans (HHIL) and use it to perform a robustness check (see Section 5.1). Data to calculate the two measures just described are provided by ABI.

9 Data on this variable and the average wage in manufacturing sectors (both these proxies used to perform robustness checks; see Sub-section 5.1) are available for 2009–2018 only. Thus, we impute their values from 2018 to 2019.

10 For instance, Santarelli et al. (2009) find a negative effect of unemployment on firms' exit, whilst Caree et al. (2011) show that unemployment and exit are positively related. Additionally, a more engaged workforce and the availability of a large pool of manufacturing employees can benefit firms, thus reducing their exit rates. However, if organized labour critically increases employees' bargaining power and recruitment costs, the impact on firms' performance can be harmful.

of industrial variety/specialization on firms' exit. On the one hand, industrial specialization can favour technological and knowledge spillovers among firms, reducing their exit rates. On the other hand, provinces characterized by greater technological variety could be less vulnerable to lock-in effects and more capable of adjusting to exogenous changes than specialized ones (Cainelli et al. 2014). The latter considerations lead us to abstain from positing an expectation on the sign of JACOB.

To control for provincial differences in the level of development, productivity and size, the estimating model encompasses the log of per-capita value added (VAPC), the ratio of export to GDP (EXP), an infrastructure index (measuring the economic and social infrastructure endowment in 2009, INFRA), and the population density (population per km^2, POP-DENS). Except for population density, which was found to have a positive effect on firms' exit rates in previous works (see Carree et al. 2011 and cited studies), we expect a negative sign for the other variables. Indeed, other things being equal, provinces offering a more favourable economic context would make market exit less likely.

Equation (3) includes a proxy of human capital – given by the provincial population share (25–64) with upper secondary, post-secondary and tertiary education (EDU) – for which we do not have clear-cut expectations on its sign, as the results of the empirical studies addressing the relationship between human capital and firms' survival seem to be inconsistent (e.g. Acs et al. 2007; Rauch and Rijsdijk 2013).

Two dummy variables, DISTRICT and CITY, account for the possibility that firms' exit rates are affected by the presence of industrial districts in a province and by the agglomeration externalities of the largest urban areas (Rome, Milan, Naples and Turin), respectively. Whilst CITY should display a negative sign (e.g. Carree et al. 2008), the expectation on the sign of DISTRICT cannot be univocal since there are no clear-cut predictions in the literature about the role of clustering of activities in a district on firms' exit (e.g. Ferragina and Mazzotta 2015).

The vector **X** also comprises the firms' entry rate in the manufacturing sector (ENTRY), computed as the ratio of newly registered firms over the stock of existing firms at time t-1, and a dummy variable coded 1 for the year 2011 – the most painful moment of the sovereign debt crisis in Italy (CRISIS)[11] – to account for firms' turnover and "turbulence" phenomena. For both, we expect a positive sign. Finally, IND_s are industry dummies, controlling for unobserved heterogeneity at the industry level,T_t is a set of time-fixed effects and ε_{pst} is the error term.

A detailed description of the variables employed in the estimations and some of their main summary statistics are reported in Table 1. Table 2 provides a correlation matrix.

4.3 Econometric methodology

Since our dependent variable is bounded on the zero value for a non-trivial number of observations, which is not the result of a truncation, we first estimate Eq. (3) by adopting a two-limit (0,100) Tobit model. However, given that EXIT may be viewed

[11] As EXIT and ENTRY are computed on firms' stock at time t–1, and the continuous regressors are all lagged once, we are precluded from gauging the impact of the financial crisis in 2009 and 2010.

Table 2 Correlation matrix

	GINI	HHID	CREDIT	UNEMPL	PARTIC	EMPLOMA	FDENS	FSIZE	JACOB	VAPC	EXP	INFRA	POPDENS
GINI	1												
HHID	–0.345	1											
CREDIT	–0.013	–0.2257	1										
UNEMPL	–0.1107	0.084	–0.391	1									
PARTIC	0.075	–0.0671	0.295	–0.7883	1								
EMPLOMA	0.064	–0.0627	0.148	–0.3205	0.327	1							
FDENS	0.002	–0.1261	0.330	–0.4022	0.412	0.204	1						
FSIZE	0.044	–0.0364	0.031	–0.1543	0.154	0.093	0.064	1					
JACOB	0.178	–0.5054	0.238	–0.0094	0.008	0.033	0.132	0.019	1				
VAPC	0.154	–0.2307	0.343	–0.7458	0.812	0.264	0.309	0.140	0.212	1			
EXP	0.138	0.008	0.036	–0.1886	0.281	0.123	0.160	0.050	–0.0103	0.218	1		
INFRA	0.216	–0.1755	0.140	–0.326	0.327	0.104	0.028	0.032	0.048	0.312	0.060	1	
POPDENS	0.080	–0.1829	0.099	–0.0148	0.036	0.036	0.077	0.010	0.297	0.265	–0.0195	0.215	1
EDU	0.167	–0.14	0.032	–0.6127	0.754	0.217	0.194	0.110	–0.0124	0.640	0.207	0.452	0.020
DISTRICT	0.113	–0.0314	0.199	–0.4145	0.387	0.212	0.499	0.076	0.206	0.253	0.109	0.100	–0.146
CITY	–0.0806	–0.0713	0.127	0.050	0.013	–0.0196	–0.0692	0.002	0.299	0.274	–0.0827	0.080	0.615
ENTRY	0.012	–0.0608	0.082	–0.1178	0.119	0.103	0.122	–0.1775	0.016	0.099	0.026	0.033	–0.0227
CRISIS	–0.1595	–0.0116	0.502	–0.2368	–0.1094	0.032	0.082	0.005	0.030	–0.0267	–0.0828	–0.0007	–0.0028
SHANNON	0.986	–0.3804	0.010	–0.1381	0.099	0.071	0.013	0.047	0.224	0.195	0.133	0.269	0.135
VAGR	0.017	–0.078	0.068	–0.1858	0.172	0.065	0.077	0.030	0.049	0.213	0.077	0.054	0.045
PVSIZE	0.061	–0.0612	–0.0212	–0.1488	0.107	0.030	–0.0515	0.035	0.328	0.211	0.059	–0.0717	0.064
WAGE	0.115	–0.0518	0.055	–0.3005	0.329	0.044	0.091	0.518	0.056	0.309	0.105	0.198	0.079
BRACLO	0.025	–0.0974	–0.242	0.064	0.073	–0.0126	–0.0488	0.005	0.073	0.130	–0.0114	0.066	0.047
HHIL	–0.3131	0.978	–0.248	0.100	–0.0747	–0.0704	–0.1341	–0.0356	–0.4697	–0.2266	–0.0023	–0.1599	–0.1571
RGDPPC	0.129	–0.2332	0.410	–0.769	0.807	0.274	0.325	0.140	0.211	0.992	0.217	0.330	0.263

Table 2 (continued)

	EDU	DISTRICT	CITY	ENTRY	CRISIS	SHAN-NON	VAGR	PVSIZE	WAGE	BRACLO	HHIL	RGDPPC
GINI												
HHID												
CREDIT												
UNEMPL												
PARTIC												
EMPLOMA												
FDENS												
FSIZE												
JACOB												
VAPC												
EXP												
INFRA												
POPDENS												
EDU	1											
DISTRICT	0.195	1										
CITY	0.030	–0.1195	1									
ENTRY	0.091	0.074	–0.0312	1								
CRISIS	–0.2686	0.001	0.001	0.037	1							
SHANNON	0.188	0.116	–0.0337	0.014	–0.1529	1						
VAGR	0.120	0.079	0.014	0.014	0.184	0.021	1					
PVSIZE	0.060	0.185	0.325	0.003	0.003	0.087	0.038	1				
WAGE	0.308	0.145	0.034	–0.2581	–0.0633	0.129	0.084	0.112	1			
BRACLO	0.182	–0.0219	0.078	–0.0139	–0.3632	0.030	0.129	–0.038	0.051	1		
HHIL	–0.1352	–0.0453	–0.0484	–0.0591	–0.0382	–0.3441	–0.0908	–0.0373	–0.0524	–0.0856	1	
RGDPPC	0.611	0.258	0.271	0.104	0.069	0.171	0.227	0.202	0.300	0.087	–0.2304	1

For the description of the variables, see Table 1 as a proportion – and to overcome the drawbacks of linear models for fractional data (i.e., OLS estimated coefficients are constant throughout the range of the relative explanatory variables, and OLS predicted values are unbounded) – we also estimate a fractional probit regression model (Papke and Wooldridge 1996; Wooldridge 2002) as a robustness check.

In a further sensitivity check, a random-effects Tobit model is run to control unobserved time-invariant heterogeneity at the sectoral-provincial level. We do not consider using a fixed-effects technique – which would allow accounting for the potential correlation between the unobserved specific effects and the regressors – because, as Wooldridge (2002) points out, the application of this technique in limited dependent-variable models might entail an incidental parameter problem, leading to inconsistent estimations with T fixed and $N \rightarrow \infty$ (see also Greene 2004). A fixed-effects approach is also unsuitable when the (key) regressors do not vary considerably over time. We have to acknowledge that this is not our case. Indeed, the consolidation process in the Italian banking system, particularly pronounced during the 1990s and the first half of the 2000s, has also been in place in the previous decade, accounting for about a quarter of all banks consolidated from 1993 (Del Prete et al. 2022). Although almost all the M&A operations in 2009–2020 involved banks belonging to the same institutional categories, such events – along with the other causes underlying the nationwide reduction of bank branches[12] – induce a non-trivial variability in our diversity indexes within provinces over the period considered.

To assess the potential endogeneity problems related to unobservable factors driving both firms' exit and local banking institutional heterogeneity and reverse causality issues (firms could self-select into provinces with more banking heterogeneity), we estimate an instrumental variable Tobit model. To find valid instruments for our key variables, we rely on the strategy adopted by Guiso et al. (2004, 2006) and followed by several other studies (e.g. Herrera and Minetti 2007; Alessandrini et al. 2009; Agostino et al. 2012; De Bonis et al. 2015;). As Guiso et al. (2004) argue, the Italian banking system's institutional and territorial structure in 1936 – the year in which, in response to the crisis of 1930–1933, strict banking regulation was introduced (which remained substantially unchanged until the early 1990s) – "was the result of historical accidents and forced consolidation, with no connection to the level of economic development at that time" (p. 946). Moreover, the 1936 regulation was not driven by different regional needs "but was random" (p. 943). Therefore, the geographical distribution of banks and branches in 1936, while it can be considered exogenous with respect to firm performance in subsequent years, is significantly correlated with the current banking landscape (Guiso et al. 2004, 2006).

Finally, we recognize that there might be "neighbourhood effects" across local credit markets for at least two reasons. First, bank branch distribution and economic conditions in nearby provinces might affect one another. Second, as business

[12] The analysis of the so-called bank de-branching phenomenon goes beyond the aim of the present work. For some contributions analysing the relevance of this phenomenon and its causes, we refer to Keil and Ongena (2020), Nguyen (2019), Carmignani and Omiccioli 2007, Carmignani et al. 2020) and Galardo et al. (2021).

relationships could network firms operating in adjacent geographical areas, institutional banking diversity – affecting firms' exit rates in a local credit market – might impact enterprises' exits in the neighbouring provinces. Resorting to spatial econometrics to capture such spillover effects is a challenging issue in our case, given the longitudinal dimension of the data and considering that some of the variables we employ, including the dependent one, are defined to the provincial-sectoral level (on the issues bedevilling applied spatial economic research see, for instance, McMillen 2010 and Gibbons and Overman 2012). Nevertheless, to assess the extent of the cross-sectional dependence across provinces, we perform the Pesaran (2021) test for panel data (with small T and large N), considering one sector at a time.[13] The results of this test are examined in the next section, which discusses our findings.

5 Results

Tables 3, 4 and 5 show the outcome of our empirical investigation. Looking at the estimation results of the benchmark model (Eq. 3), reported in column 1 of Table 3, the estimated coefficient of GINI appears to be negative and statistically significant at the 1% level – thus suggesting that banking institutional diversity reduces firms' propensity to exit the market.[14] We believe such a finding is evidence in favour of the biodiversity argument discussed in Section 2, as it indicates that a greater variety of institutional models in the banking landscape does matter in helping firms to persist with their businesses. In other words, our results seem to be in accord with the central conclusion of Ayadi et al. (2009, 2010) that – beyond the merits of any particular bank model – the coexistence of a wide array of credit institutions having different business strategies and lending policies is indeed, which is important for supporting the real economy. Therefore, as a policy implication, our analysis sustains the view (e.g. Ferri 2010; Ferri and Neuberger 2018) that regulatory authorities should promote actions to preserve and promote diversity in the banking sector.[15]

Passing now to briefly consider the results of the control variables, the estimated parameters of CREDIT, FSIZE, EXP, ENTRY, and CRISIS are all statistically significant and display the expected signs. FDENS enters significantly with a negative sign, indicating that firms' organizational and spatial proximity benefit their performance. The negative coefficient of HHID would suggest – according to a strand of the research on banking market structure (e.g. Petersen and Rajan 1995; Shaffer 1998; Cao and Shi 2001; Marquez 2002) – that a lower concentration (more intense competition) of local credit markets is detrimental for firms, although this coefficient appears statistically

[13] For the tobacco sector, the observations in the estimating sample are insufficient to perform the test. Indeed, for this sector, the massive amount of zero values for the variable "ceased firms" led to about 80% of missing values of EXIT.

[14] In the limited dependent-variable models we adopt, the estimated coefficients gauge the marginal impact of each regressor on a latent variable which, in our analysis, is the firm's propensity to exit the market.

[15] Discussing the role of banking diversity within the joint process of Capital Markets Union (CMU) and Banking Union (BU), Ferri and Neuberger (2018) conclude that both CMU and BU have, in various ways, impaired banking diversity, sharing a bias towards transaction banking.

significant at the conventional level only in column 7 of Table 3. Regarding the agglomeration economies, our results confirm their role in explaining the exit of manufacturing firms in Italy, a country historically characterized by firms' persistence in agglomerated contexts, such as local industrial clusters and urban areas. Indeed, the JACOB index displays a positive and significant coefficient, suggesting that a wider provincial sectorial variety (a lower industrial specialization) might lead to higher firms' exit rates.[16] The latter, according to our figures, are also higher in areas with industrial districts – where firm dynamics are more vigorous (e.g. Carree et al. 2008; Santarelli et al. 2009; Ferragina and Mazzotta 2015)[17] – whereas they are lower in larger cities, likely because urbanization economies are at work (e.g. McCann 2008). The results on the variables EMPLOMA and PDENS align with those of other works (e.g. Carree et al. 2011; Iwasaki et al. 2016), and the positive sign of the human capital parameter might suggest that the firms exiting is higher in regions with more educated workforces – since in such areas there tends to be a higher rate of start-ups (Parker 2018), whose survival rates are impressively low (e.g. Colombelli et al. 2016). The estimated coefficients of the remaining variables are found to be statistically insignificant.

In closing this section, we discuss the results of the Pesaran test reported in Table 6 (in the Appendix). They indicate that for most sectors, in about 70% of cases, the null hypothesis of independence across provinces cannot be rejected at the conventional 5% level. While providing evidence that corroborates the estimators we adopted, these figures raise the question of the potential reasons why, in the remaining 30% of cases, the exit of manufacturing firms seems to be significantly influenced by spatial or spillover effects in our sample.[18] To address this question, we first note that the Pesaran test rejects the null hypothesis for those Italian manufacturing sectors traditionally characterized by relevant intra- and inter-sectoral spillovers, such as clothing (e.g. Dunford 2006), wood products (e.g. Forni and Paba 2002), manufacturing of basic metals (e.g. Kataishi et al. 2021), repairing and installation of machinery and manufacture of other transport equipment (e.g. Aiello and Cardamone 2008), coke and refined petroleum products (e.g. Gong 2018) and printing and reproduction of recorded media. This picture leads us to speculate that, besides the considerations offered at the end of Sub-section 4.3, it could be the dense web of production links among firms operating in these industries that drives the cross-sectional dependence detected in our sample. Indeed, as a possibility, strong firms' connections in a sector might facilitate the rise of network relationships. These, in turn, can either facilitate firms' financing – as they could increase firms' reputation, provide cross-guarantee of debt (e.g. Scalera and Zazzaro 2011) and covey *informational content* for lenders (e.g. Agostino and Trivieri

[16] This finding seems to support the *specialisation view* of the literature on agglomeration economies and firms' exit, according to which in areas where production structures, labour market and local value chains are industry-specialised, and as they allow for knowledge to spillover between similar firms, exit rates tend to be lower (e.g. Cainelli et al. 2014; Duranton and Puga 2004).

[17] This result is also coherent with the ENTRY parameter, found to be positive and significant. Both entry and exit rates are likely higher in provinces with industrial districts. The entry of new, more productive firms can influence the propensity of old firms to exit in the process of local creative destruction (e.g. Pèer and Vertinsky 2008).

[18] For a discussion on how different types of spillovers (and their transmission mechanisms) may mitigate firms' exit, see, for instance, Ferragina and Mazzotta (2015).

2014) – or adversely affect access to credit if lenders expect that firms' connections could act as a potential crisis contagion mechanism (e.g. Battiston et al. 2007; Cainelli et al. 2014). In both cases, interfirm links might lead to spatial spillover implications when analysing the role of banking diversity on firms' exit.

5.1 Robustness checks

To assess the robustness of our results, we perform several sensitivity checks. Those carried out by modifying our benchmark model are reported in columns 2–7 of Table 3. Following Santarelli et al. (2009), we first add to Eq. (3) the value-added growth rate at the provincial level (VAGR; column 2) and then the average wage in manufacturing sectors (WAGE; column 3). In column 4, we add the variable PVSIZE (the number of municipalities in a province) to control for the physical dimension of the local credit markets. Further, to account, at least partially, for the effects related to the Italian banking industry's structural transformations mentioned in Sub-section 4.3, we include in the econometric model the provincial ratio of closed branches over the total branches (CLOBRA; column 5).[19] Finally, in column 6, we replace the HHID with the Herfindahl–Hirschman index on loans (HHIL), and, in column 7, the provincial real per-capita gross domestic product (RGDPPC) replaces the per-capita value added. The econometric results of all these checks strongly support the finding that local banking diversity significantly reduces the firms' propensity to exit the market.[20]

A consistent pattern also emerges when changing the adopted estimator or the explanatory variable of interest, as shown in Table 4. Column 1 reports the fractional probit estimations, while column 2 displays the results using a random-effects Tobit model. Further, column 3 shows the estimates obtained when employing an IV Tobit technique to deal with the endogeneity issue of the diversity index. As argued in Sub-section 4.3, following the strategy adopted by Guiso et al. (2004, 2006), we retrieve the instrumental variables for our key regressors considering the Italian banking system's institutional and territorial (provincial) structure in 1936. In detail, the null hypothesis of the Amemiya–Lee–Newey test of overidentified restrictions cannot be rejected when, as instruments, we use the shares of branches owned by commercial banks (the square of this variable) and *Popolari* banks. However, looking at the Wald statistic's value, reported at the bottom of Table 4, the null hypothesis of the exogeneity of GINI cannot

[19] To obtain the numerator of this ratio, we rely on the Bank of Italy GIAVA database, which provides information on all the Italian bank branches from 1936, comprising the dates of their opening and closing. To rule out the possibility of including in CLOBRA those branches that, owing to bank mergers and acquisitions, are registered around the same time as closed and opened, we take a prudential approach and drop the (GIAVA) observations reporting – for both opening and closing occurrence – the description "structural events among intermediaries."

[20] As an additional robustness check, we include in Eq. (3) the provincial ratio of innovative start-ups at time t over the stock of existing firms at time t–1, considering that start-ups usually face more binding financial constraints. We resort to the Bureau van Dijk AIDA (*Analisi Informatizzata delle Aziende Italiane*) databank to retrieve information on the number of these firms. In the version we interrogate, AIDA provides data for 2015–2020 and, for this period, contains information on 9763 start-ups, of which 1577 are in the manufacturing sectors. The output of these estimations – not reported but available upon request – qualitatively confirms our main finding.

Table 3 Estimation results: Benchmark model and robustness checks

	1 Benchmark model	2 Adding VAGR	3 Adding WAGE	4 Adding PVSIZE	5 Adding CLOBRA	6 HHIL instead of HHID	7 RGDPPC instead of VAPC
GINI	– 0.9978***	– 0.9926***	– 0.9651***	– 0.9983***	– 0.9955***	– 0.9503***	– 0.9598***
	[0.27185]	[0.27175]	[0.27262]	[0.27188]	[0.27181]	[0.27041]	[0.27112]
HHID (Herfindahl–Hirschman index on deposits)	–1.1126	–1.104	–0.8795	–1.1165	–1.0948		–1.3233*
	[0.75146]	[0.75124]	[0.75272]	[0.75696]	[0.75215]		[0.75542]
CREDIT (loans/deposits)	–0.0028**	–0.0028**	–0.0031***	–0.0028**	–0.0028**	–0.0025**	–0.0028**
	[0.00112]	[0.00112]	[0.00111]	[0.00114]	[0.00112]	[0.00113]	[0.00111]
UNEMPL (unemploymentrate)	–0.0183	–0.0176	–0.0222	–0.0183	–0.0182	–0.0168	–0.0201
	[0.01346]	[0.01348]	[0.01356]	[0.01346]	[0.01346]	[0.01343]	[0.01340]
PARTIC (participation rate)	–0.0158	–0.0156	–0.0215*	–0.0158	–0.0154	–0.0165	–0.0134
	[0.01141]	[0.01141]	[0.01140]	[0.01152]	[0.01145]	[0.01141]	[0.01131]
EMPLOMA (employees in manufacturing)	0.5004***	0.5009***	0.5248***	0.5004***	0.5004***	0.4998***	0.4887***
	[0.06394]	[0.06394]	[0.06431]	[0.06394]	[0.06394]	[0.06394]	[0.06440]
FDENS (firm density)	–0.2899**	–0.2878**	–0.2820**	–0.2899**	–0.2869**	–0.2793**	–0.2814**
	[0.13787]	[0.13791]	[0.13816]	[0.13782]	[0.13806]	[0.13785]	[0.13747]
FSIZE (firm size)	–0.5542***	–0.5551***	–0.5319***	–0.5542***	–0.5541***	–0.5531***	–0.5092***
	[0.11767]	[0.11765]	[0.12518]	[0.11767]	[0.11766]	[0.11767]	[0.11962]
JACOB (Jacob index)	0.1137***	0.1131***	0.1156***	0.1143***	0.1129***	0.1222***	0.1087***
	[0.02068]	[0.02071]	[0.02084]	[0.02368]	[0.02076]	[0.02037]	[0.02085]
VAPC (value added per capita)	0.4872	0.5320	0.5805*	0.4886	0.4683	0.5544*	
	[0.33180]	[0.33454]	[0.33046]	[0.33575]	[0.33402]	[0.32914]	
EXP (expor/GDP)	–0.0035**	–0.0035**	–0.0032**	–0.0035**	–0.0034**	–0.0035**	–0.0035**
	[0.00142]	[0.00142]	[0.00144]	[0.00142]	[0.00142]	[0.00142]	[0.00142]

Table 3 (continued)

	1	2	3	4	5	6	7
	Benchmark model	Adding VAGR	Adding WAGE	Adding PVSIZE	Adding CLOBRA	HHIL instead of HHID	RGDPPC instead of VAPC
INFRA (infrastructure endowment index)	0.0065	0.0064	0.0066	0.0065	0.0063	0.0070	0.0060
	[0.00491]	[0.00491]	[0.00494]	[0.00497]	[0.00493]	[0.00491]	[0.00490]
POPDENS (population density)	0.2713***	0.2715***	0.2544***	0.2698***	0.2696***	0.2838***	0.2673***
	[0.05773]	[0.05773]	[0.05714]	[0.06645]	[0.05779]	[0.05749]	[0.05756]
EDU (post-upper secondary and tertiary education)	0.0495*	0.0495*	0.0528*	0.0494*	0.0493*	0.0542*	0.0522*
	[0.02815]	[0.02815]	[0.02823]	[0.02820]	[0.02816]	[0.02814]	[0.02809]
DISTRICT (industrial districts)	0.2236***	0.2239***	0.2154***	0.2241***	0.2230***	0.2062***	0.2239***
	[0.07608]	[0.07607]	[0.07564]	[0.07728]	[0.07610]	[0.07603]	[0.07596]
CITY (largest cities)	–0.4326***	–0.4434***	–0.4890***	–0.4303**	–0.4328***	–0.4872***	–0.3865**
	[0.16574]	[0.16582]	[0.16332]	[0.17012]	[0.16571]	[0.16419]	[0.16505]
ENTRY (newly registered firms)	0.1901***	0.1900***	0.1905***	0.1901***	0.1901***	0.1901***	0.1948***
	[0.01602]	[0.01603]	[0.01614]	[0.01603]	[0.01603]	[0.01603]	[0.01610]
CRISIS (sovereign debt crisis: 2011 = 1)	1.6489***	1.6727***	1.7284***	1.6489***	1.6665***	1.6873***	1.5989***
	[0.26603]	[0.26698]	[0.26757]	[0.26603]	[0.26756]	[0.26534]	[0.26073]
VAGR (value-added growth rate)		–0.0107					
		[0.01251]					
WAGE (average wage in manufacturing)			–0.135				
			[0.17456]				
PVSIZE (provincial size)				0.0034			
				[0.07104]			

Table 3 (continued)

	1	2	3	4	5	6	7
	Benchmark model	Adding VAGR	Adding WAGE	Adding PVSIZE	Adding CLOBRA	HHIL instead of HHID	RGDPPC instead of VAPC
CLOBRA (closed bank branches/ total branches)					0.0295		
					[0.05729]		
HHIL (Herfindahl–Hirschman index on loans)						–0.1761	
						[0.66012]	
RGDPPC (real GDP per capita)							0.4008
							[0.33367]
Observations	22,468	22,468	21,962	22,468	22,468	22,468	22,050
Left-censored obs.	3973	3973	3722	3973	3973	3973	3807
Model test	79.41	78.27	155.26	78.28	78.24	79.42	79.47
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

For a broader description of the variables, see Table 1. The dependent variable is EXIT. Superscripts ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively. The standard errors, reported in square brackets, are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias, except dummies and INFRA. The variables EMPLOMA, FDENS, FSIZE, VAPC, POPDENS, WAGE, PVSIZE and RGDPPC are in log terms. Year, sectoral, and regional dummies are always included but not reported. The model test is the F-test of joint significance of all explanatory variables (p values in italics). Left-censored obs. are the zero-value observations in the estimating sample.

Table 4 Estimation results: Changing estimator and key variable

	1 FRACREG	2 XTTOBIT	3 IVTOBIT	4 Changing the key variable
GINI	–0.00764***	–1.0093***	–3.6499*	
	[0.00224]	[0.28824]	[1.94039]	
SHANNON				–0.5999***
				[0.17456]
PCAM (principal component analysis measure)				
HHID (Herfindahl–Hirschman index on deposits)	–0.00809	–0.6621	–1.9012**	–1.1565
	[0.00627]	[0.73919]	[0.83077]	[0.75438]
CREDIT (loans/deposits)	–0.00003***	–0.0030**	–0.0023*	–0.0029***
	[0.00001]	[0.00132]	[0.00142]	[0.00112]
UNEMPL (unemployment rate)	–0.00018	–0.0221*	–0.0376**	–0.0191
	[0.00011]	[0.01345]	[0.01682]	[0.01349]
PARTIC (participation rate)	–0.0001	–0.0132	0.0108	–0.0154
	[0.00010]	[0.01328]	[0.01385]	[0.01144]
EMPLOMA (employees in manufacturing)	0.00260***	0.5653***	0.5499***	0.5004***
	[0.00052]	[0.07486]	[0.05052]	[0.06394]
FDENS (firm density)	–0.00264**	–0.2247	–0.5743***	–0.3004**
	[0.00114]	[0.16269]	[0.16332]	[0.13802]
FSIZE (firm size)	–0.00286***	–0.6195***	–0.6982***	–0.5547***
	[0.00105]	[0.11043]	[0.05908]	[0.11767]
JACOB (Jacob index)	0.00046***	0.1354***	0.1523***	0.1142***
	[0.00017]	[0.02204]	[0.03841]	[0.02072]
VAPC (value-added per capita)	0.0023	0.4911	0.3801	0.4929
	[0.00276]	[0.39970]	[0.34391]	[0.33170]
EXP (export/GDP)	–0.00003**	–0.0031**	–0.0007	–0.0035**
	[0.00001]	[0.00127]	[0.00183]	[0.00142]
INFRA (infrastructure endowment index)	0.0000	0.0055	– 0.0005	0.0060
	[0.00004]	[0.00619]	[0.00424]	[0.00491]
POPDENS (population density)	0.00213***	0.2917***	0.1405	0.2829***
	[0.00047]	[0.06880]	[0.09500]	[0.05755]
EDU (post-upper secondary and tertiary education)	0.00047**	0.0499*	–0.0548	0.0484*
	[0.00023]	[0.02664]	[0.04175]	[0.02829]
DISTRICT (industrial districts)	0.00185***	0.2231**	0.1279	0.2249***
	[0.00062]	[0.09635]	[0.09221]	[0.07610]
CITY (largest cities)	–0.00387***	–0.4607*	–0.6841***	–0.4180**
	[0.00137]	[0.23748]	[0.24850]	[0.16551]
ENTRY (newly registered firms)	0.00142***	0.1386***	0.2075***	0.1901***
	[0.00012]	[0.01269]	[0.01161]	[0.01602]
CRISIS (sovereign debt crisis)	0.01537***	1.6961***	0.4441	1.6588***
	[0.00222]	[0.26154]	[0.65680]	[0.26669]
Observations	22,468	22,468	19,580	22,468

Table 4 (continued)

	1 FRACREG	2 XTTOBIT	3 IVTOBIT	4 Changing the key variable
Left-censored obs.		3973	3265	3973
Model test	4511	4262	5232	79.41
	0.0000	*0.0000*	*0.0000*	*0.0000*
Wald test of exogeneity			1.410	
			0.2355	
Test of overid. restrictions: (Amemiya-Lee-Newey Chi-sq.)			4.363	
			0.2248	

For a broader description of the variables, see Table 1. The dependent variable is EXIT (EXIT/100 in column 1). Superscripts ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively. The standard errors, reported in square brackets, are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias, except dummies and INFRA. The variables EMPLOMA, FDENS, FSIZE, VAPC and POPDENS are in log terms. Year, sectoral and regional dummies are always included but not reported. The model test is the Wald-Chi^2 test (the *F*-test in column 4) of joint significance of all explanatory variables (*p* values in italics). Left-censored obs. are the zero-value observations in the estimating sample. The instrumental variables used in the IVTOBIT estimation (column 3) are the shares of provincial branches owned in 1936 by commercial banks (the square of this variable) and *Popolari* banks. The null hypothesis of the Wald test of exogeneity is that the key regressor (GINI) is exogenous, while the null hypothesis of the Amemiya–Lee–Newey test is that all the instruments are exogenous (*p* values of both tests are reported in italics).

be rejected at the conventional levels, indicating that previously adopted estimators deliver meaningful results. Therefore, we do not emphasise the outcome of the IV estimation.[21] Finally, the last column of Table 4 reports the estimates attained when replacing GINI with the Shannon index (SHANNON), also described in Section 3.

All these additional robustness checks confirm, once more, our findings that a higher institutional banking diversity in local credit markets tends to lower firms' exit rates, thus corroborating our previous discussion on the importance of having a plurality of different institutional and organizational forms in the banking sector.

5.2 Banking diversity in crisis time

To deepen the analysis, we assess the impact of banking diversity on firms' exit rates during two turmoil periods: the financial–sovereign debt crisis and the first year of the COVID-19 pandemic emergency.[22] Focusing on the former period, we estimate Eq. (3) by including an interaction term between the dummy CRISIS and the GINI

[21] The first-stage results of the IV Tobit estimation are reported in the Appendix (Table 7)

[22] For contributions investigating the effects of the financial crisis on firms' exit, see, for instance, Carreira and Teixeira (2016) and Martinez et al. (2019). For some analysis of the economic effects of the COVID-19 pandemic on entrepreneurship and small businesses, we refer to the recent papers in Belitski et al. (2022).

index (labelled GICR). CRISIS is coded 1 for 2011, the most severe year of the sovereign debt crisis in Italy, and 0 for the other years. The estimation results, reported in column 1 of Table 5,[23] indicate that a higher local banking diversity would have mitigated the adverse impact of the sovereign debt turmoil on firms' exit rates. Indeed, the estimated coefficients of GINI and GICR are both negative and statistically significant. In addition – when, following Brambor et al. (2006), we compute and test the marginal effects of GINI+GICR – it is also found negative and statistically significant (see the final rows of Table 5), suggesting that the beneficial effect of banking diversity on firms' exit would have been even stronger during the last great recession.[24]

Even these latter findings seem to align with the biodiversity argument. Indeed, they suggest that in a scenario characterised by great financial turmoil and uncertainty, such as the one caused by the double-dip crisis that occurred in the late 2000s, a banking sector populated by many different bank types might contribute to developing an institutional environment favourable for firms' resilience. Furthermore, this indication strongly supports the perspective that the recent financial–sovereign debt crisis has underscored the necessity of preserving and supporting institutional pluralism within the European banking sector.

In passing, we note that the estimated coefficients of the temporal dummies in Table 5 indicate that, as expected, the repercussions of the financial–sovereign debt crisis on firms' exits were burdensome in the immediately following years, attenuating during the decade. This picture appears in line with the documented trend registered in Italy in the aftermath of the 2009 crisis (e.g. Cerved 2015; Landini et al. 2020) and, doubtless, reflects the policy responses adopted at the international and national levels to contrast the recession. How these policies, among which the changes that occurred in the EU banking regulation and supervision (e.g. Bank for International Settlements 2018), can be integrated into the framework of our analysis – so as to provide a more fine-grained assessment of the role of banking institutional variety in helping firms to recover from the double-dip recession – is an issue we intend to assess in future research

Our evidence is much less sharp when considering column 2 of Table 5, which displays the estimation results of the benchmark model augmented with the interaction term between the dummy COVID, coded 1 for 2020 and 0 otherwise, and GINI (this interaction term is labelled GICV). We now find that – though the estimated coefficients of GINI and GIVC are individually statistically significant – the overall marginal effect of GINI + GICV is not. These figures indicate that, differently from the financial–sovereign debt crisis scenario, banking diversity would not have had a sharper impact on firms' exit rates during 2020.

On these last results, a note of great caution is in order. Indeed, as our data only capture the very first phase of the COVID-19 pandemic crisis – and considering that

[23] In both the estimations reported in this table, the dummy year 2019 is omitted to avoid collinearity.

[24] The estimated coefficient of GINI may be interpreted as the impact of our measure of banking institutional diversity on the propensity of firms' exit in the non-crisis time. The marginal effect of GINI + GICR is the estimated impact of the diversity index on the propensity of firms' exit during the (worst year of) financial–sovereign debt crisis.

Table 5 Financial–sovereign and COVID-19 crises

	1 Financial–sovereign crisis	2 COVID-19
GINI	–0.8741***	–1.1306***
	[0.27915]	[0.28168]
CRISIS (sovereign debt crisis: 2011 = 1)	1.1892***	0.7842***
	[0.32432]	[0.25291]
GINI*CRISIS (GICR)	–1.1480**	
	[0.55445]	
COVID (COVID-19 outburst: 2020 = 1)	–0.8644***	–1.3887***
	[0.11379]	[0.30529]
GINI*COVID (GICV)		1.0727*
		[0.56896]
HHID (Herfindahl–Hirschman index on deposits)	–1.0854	–1.1086
	[0.75181]	[0.75134]
CREDIT (loans/deposits)	–0.0028**	–0.0026**
	[0.00112]	[0.00112]
UNEMPL (unemployment rate)	–0.017	–0.0181
	[0.01347]	[0.01346]
PARTIC (participation rate)	–0.0158	–0.0166
	[0.01141]	[0.01141]
EMPLOMA (employees in manufacturing)	0.5002***	0.4998***
	[0.06392]	[0.06392]
FDENS (firm density)	–0.2844**	–0.2885**
	[0.13786]	[0.13784]
FSIZE (firm size)	–0.5558***	–0.5551***
	[0.11766]	[0.11768]
JACOB (Jacob index)	0.1128***	0.1126***
	[0.02068]	[0.02069]
VAPC (value added per capita)	0.4968	0.4949
	[0.33185]	[0.33183]
EXP (export/GDP)	–0.0035**	–0.0034**
	[0.00142]	[0.00142]
INFRA (infrastructure endowment index)	0.0069	0.0074
	[0.00491]	[0.00493]
POPDENS (population density)	0.2699***	0.2719***
	[0.05772]	[0.05772]
EDU (post-upper secondary and tertiary education)	0.0471*	0.0539*
	[0.02817]	[0.02823]
DISTRICT (industrial districts)	0.2232***	0.2240***
	[0.07610]	[0.07605]
CITY (largest cities)	–0.4300***	–0.4401***
	[0.16583]	[0.16580]

Table 5 (continued)

	1 Financial–sovereign crisis	2 COVID-19
ENTRY (newly registered firms)	0.1900***	0.1901***
	[0.01602]	[0.01602]
Year dummy_2012	0.8900***	0.9060***
	[0.21824]	[0.21818]
Year dummy_2013	0.7354***	0.7506***
	[0.18219]	[0.18212]
Year dummy_2014	0.3115*	0.3294**
	[0.15958]	[0.15955]
Year dummy_2015	0.2284*	0.2468*
	[0.13715]	[0.13710]
Year dummy_2016	0.0468	0.0585
	[0.12749]	[0.12746]
Year dummy_2017	–0.2638**	–0.2645**
	[0.12200]	[0.12192]
Year dummy_2018	– 0.3382***	– 0.3626***
	[0.12225]	[0.12230]
Year dummy_2019	*(omitted)*	*(omitted)*
Observations	22,468	22,468
Left-censored obs.	3,973	3,973
Model test	78.31	78.36
	0.0000	*0.0000*
F-test [GINI, GICR (GICV)]	9.01	8.42
	0.0000	*0.0000*
[GINI+GICR(GICV)]	–2.0221119	–0.05788326
t test [GINI+GICR(GICV)]	3.61	0.10
	0.0002	*0.5409*

For a broader description of the variables, see Table 1. The dependent variable is EXIT. Superscripts ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively. The standard errors, reported in square brackets, are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias, except dummies and INFRA. The variables EMPLOMA, FDENS, FSIZE, VAPC and POPDENS are in log terms. Sectoral and regional dummies are always included but not reported. The model test is the *F*-test of the joint significance of all explanatory variables. Left-censored obs. are the zero-value observations in the estimating sample. The variable GICR (GICV) is the interaction term between the dummy CRISIS (COVID) and GINI. The statistical significance of the sum of random variables [GINI+ GICR (GICV)] is assessed by computing the relative standard errors. The p-values of the *F*- and *t* tests are reported in italics.

it has been characterised by unprecedented policy interventions that could substantially bias our estimates [25] – the figures in column 2 of Table 5 should not be emphasised. Evaluating them as the output of a preliminary attempt to explore the issue, which calls for further in-depth research.

6 Conclusion

With Italian data at the local credit markets level, this paper has investigated the role of banking diversity on firms' exit in the past decade. Underlying our analysis is the central proposition of the "biodiversity argument", stating that the coexistence of a broad mix of different credit institutions matters for supporting the real economy – beyond the strengths and weaknesses of any institutional bank type. From this perspective, the biodiversity view might provide insights going over the mixed picture of predictions offered by the extant literature on the effects of banking heterogeneity, which, indeed, mainly focuses on the merits and pitfalls of one bank model over another.

According to our results, institutional banking diversity would have reduced firms' exit rates in the investigated period, and the beneficial effect would have been even stronger during the last financial–sovereign debt crisis. We believe that both of these findings support the biodiversity viewpoint, as they suggest that a banking landscape populated by a variety of institutional models does matter in shaping an environment favourable for firms' resilience, especially in a scenario characterised by financial turmoil and uncertainty. As a policy recommendation stemming from these considerations, authorities should promote regulations that, avoiding bias towards a specific bank model, aim to preserve and promote biodiversity in the banking sector.

To conclude, we point out some limitations of this study, projecting them as issues for future research. The first and likely major flaw of our analysis is the lack of a proper theoretical framework, which prevented us from formulating an expectation about the specific effect of banking diversity on firms' financing and exit. Given its demanding nature, working toward overcoming such a limitation is a task of our ongoing research – aware that, as it stands, the present contribution is essentially explorative in nature.

Another item of our research agenda is to investigate banking diversity under the two profiles embedded in the index(es) employed here: the *richness* one, grasping the range of bank footprints, and the *evenness* profile, reflecting the degree of equality in the bank types distribution. Disentangling these two profiles – which is challenging on methodological grounds – could provide more fine-grained insights into the role of banking diversity, leading to additional policy recommendations.

[25] Governments worldwide have deployed a range of actions to cushion the effects of the economic shock brought on by COVID-19. Several measures have been adopted at the international, national and local levels to prevent companies from failing, with the idea of helping them "hibernate" until recovery. Some researchers have proposed "hibernating" to avoid the economic costs of breaking firms' valuable relationships with their stakeholders and going into bankruptcy (Didier et al. 2021). In a recent study, the Bank of Italy reported a 33% decrease in bankruptcy applications and a 27% decrease in firm exits during 2020–2021 compared to 2019 (Giacomelli et al. 2022).

Finally, as already mentioned, in prospective research, we aim to investigate the role of banking diversity in depth during the COVID-19 pandemic crisis and in its aftermath, as well as develop our analysis by taking an international perspective.

Appendix

Table 6 Pesaran test results

	Using the Gini index	
MANUFACTURING SECTORS (NACE Rev. 2)	test	*p* value
Manufacture of food products	–1.743	0.0813
Manufacture of beverages	–1.237	0.2162
Manufacture of textiles	–1.387	0.1656
Manufacture of wearing apparel	–2.083	0.0372
Manufacture of leather and related products	–0.051	0.9596
Manufacture of wood and of products of wood and cork, except furniture	–1.916	0.0497
Manufacture of paper and paper products	–1.211	0.2261
Printing and reproduction of recorded media	–2.028	0.0426
Manufacture of coke and refined petroleum products	–2.918	0.0035
Manufacture of chemicals and chemical products	–1.833	0.0668
Manufacture of basic pharmaceutical products and pharmaceutical preparations	–0.498	0.6185
Manufacture of rubber and plastic products	–0.989	0.3227
Manufacture of other non-metallic mineral products	–1.769	0.0769
Manufacture of basic metals	–2.026	0.0428
Manufacture of fabricated metal products, except machinery and equipment	–1.598	0.1101
Manufacture of computer, electronic and optical products	–1.726	0.0843
Manufacture of electrical equipment	–1.578	0.1145
Manufacture of machinery and equipment n.e.c.	–1.735	0.0827
Manufacture of motor vehicles, trailers and semi-trailers	–1.433	0.1519
Manufacture of other transport equipment	–2.021	0.0432
Manufacture of furniture	–1.338	0.1809
Other manufacturing	–1.683	0.0923
Repair and installation of machinery and equipment	–1.971	0.0487

Table 7 IVTOBIT estimation: First-stage results

	Coefficient	Std. err.	t	*P*>|t|
COMBB_36 (commercial banks' share of branches in 1936)	-0.0008	0.00025	–3.34	*0.0010*
COMBB_36 ^{2}	0.00003	0.00001	6.11	*0.0000*
PBB_1936 (*Popolari* banks' share of branches in 1936)	-0.0023	0.0001	–19.3	*0.0000*
HHID (Herfindahl–Hirschman index on deposits)	-0.0642	0.0175	–3.67	*0.0000*
CREDIT (loans/deposits)	0.0004	0.0000	14.33	*0.0000*
UNEMPL (unemployment rate)	-0.0064	0.0003	–19	*0.0000*
PARTIC (participation rate)	0.0047	0.0003	15.9	*0.0000*
EMPLOMA (employees in manufacturing)	0.0032	0.0012	2.6	*0.0090*
FDENS (firm density)	-0.0032	0.0041	–0.78	*0.4370*
FSIZE (firm size)	-0.0010	0.0014	–0.69	*0.4870*
JACOB (Jacob index)	0.0077	0.0006	12.66	*0.0000*
VAPC (value added per capita)	0.0115	0.0085	1.35	*0.1760*
EXP (export/GDP)	0.0005	0.0000	14.18	*0.0000*
INFRA (infrastructure endowment index)	0.0021	0.0001	17.35	*0.0000*
POPDENS (population density)	-0.0100	0.0017	–5.79	*0.0000*
EDU (post-upper secondary and tertiary education)	-0.0223	0.0004	–50.4	*0.0000*
DISTRICT (industrial districts)	-0.0116	0.0021	–5.56	*0.0000*
CITY (largest cities)	-0.1302	0.0051	–25.4	*0.0000*
ENTRY (newly registered firms)	-0.0001	0.0003	–0.26	*0.7990*
CRISIS (sovereign debt crisis: 2011 = 1)	-0.3411	0.0051	–67.39	*0.0000*
Observations	19,580			
Model test	535.10			
	0.0000			
R-squared	0.6296			
Adj *R*-squared	0.6284			

The dependent variable is GINI. Superscripts ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively. Year, sectoral and regional dummies are always included but not reported. The model test is the *F*-test of joint significance of all explanatory variables (*p* values in italics)

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Data availability The dataset generated and analysed during the current study is not publicly available since it constitutes an excerpt of research in progress. However, other than data from third parties, it is available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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