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Diversity in banking and new firm formation. Insights from the Italian local credit markets

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A B S T R A C T

This paper empirically investigates the role of bank structural characteristics on firms' creation in the Italian local credit markets from 2009 to 2020. By departing from the existing research, our analysis takes the perspective of the so-called "biodiversity argument" in banking (Ayadi et al., 2009, 2010). As this viewpoint echoes insights from the ecological sciences, we measure bank diversity by retrieving two "biodiversity" indexes: the Gini-Simpson index and, for robustness, the Shannon index. Our results suggest that the coexistence of different institutional models in the banking landscape benefits the formation of new firms – especially those taking the legal form of limited liability companies, as innovative start-ups. We also find that, at the outbreak of the COVID-19 crisis, bank diversity might have mitigated the adverse effects of the pandemic turmoil. Our policy recommendation is that authorities design regulations to encourage institutional variety in the banking market.

1. Introduction

A sizable part of the literature investigating the drivers of entrepreneurship (e.g., Parker, 2018; Verheul et al., 2002) focuses on the financing sources for nascent firms and the role played by banks.[1] In this respect, an open research debate concerns the relevance of banks' structural and organizational characteristics. According to some contributions, small banks (local, single-market, typically stakeholder-value institutions), exploiting the knowledge of the local economy and their organizational structures characterized by few management layers, would have an advantage over large (nonlocal, multimarket, shareholder-value institutions) in collecting and using *soft information* (e.g., Liberti & Mian, 2009; Stein, 2002)[2] – and, thus, in forging lending relationships that are crucial for the financing of firms suffering more intense information asymmetries (Berger et al., 2015, 2017; Berger & Udell, 2002; Cole et al., 2004; Mkhaiber & Werner, 2021; Petersen & Rajan, 1994; Scott, 2004).

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[1] As argued by Cassar (2004), "how business start-ups are financed is one of the most fundamental questions of enterprise research" (p. 262). It is a question that presents peculiar features, as start-ups are typically low-scale, with many intangibles and knowledge-based assets (Hsu, 2004) and, above all, they are informationally opaque for lenders, lacking prior operating history or reputation, and facing high failure risk (e.g., Berger & Udell, 1998; Huyghebaert & Van de Gucht, 2007).

[2] This information is qualitative and confidential in nature and, unlike that attainable from written records, is difficult or costly to summarize in numeric scores. For more on what is meant by soft and hard information, see Liberti and Petersen (2019).

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Other studies claim that the paradigm by which small banks are advantaged in lending to opaque firms is misleading. For instance, Bartoli et al. (2013) assert that "complementarity among transactions and relationship lending technologies is indeed a prevailing phenomenon, compared to specialization in one primary lending technology, and that complementarity is higher for large banks compared to small local banks." (p. 5477). Black and Strahan (2002) provide evidence that large banks' superior ability to diversify credit risks across borrowers allows them to reduce agency lending costs and, thus, finance risky and opaque firms at better conditions than smaller banks. Not least, by exploiting the rapid ICT advances, large banks can finance informationally opaque firms by using transaction technologies such as credit scoring, asset-based lending, factoring, fixed-asset lending and leasing (e.g., Berger et al., 2005, 2014; Berger & Udell, 2006; Carter & McNulty, 2005; De Young et al., 2011; Frame et al., 2001; Petersen & Rajan, 2002).

The above brief overview suggests that the research on which bank type is more suitable for financing risky firms provides an inconclusive picture, thus calling for a different conceptual perspective. In this paper, we contend that such a perspective may be offered by the so-called "biodiversity argument" in banking, pioneered by Ayadi et al. (2009 and 2010) and advocated in several other studies (e.g., Baum et al., 2020; Costanzo et al., 2023; Ferri & Neuberger, 2018; Kalmi, 2017; Kotz & Schäfer, 2018; Michie, 2011; Michie & Oughton, 2022; Miklaszewska, 2017). By embracing this viewpoint and using Italian data, we aim to empirically investigate to what extent banking diversity is relevant for new firms' formation. To the best of our knowledge, this issue has not been assessed so far, and we believe it might provide insights going over the mixed findings of the extant literature.

A central proposition of the biodiversity viewpoint is that a landscape populated by a variety of bank models – different in terms of institutional configurations, organizational structures, business strategies and lending technologies – is of critical importance for ensuring the financing of the real economy, as well as the stability of the banking system itself. Indeed, since economies are complex and intrinsically unpredictable systems, there is no way to know which model will prove to be superior in all possible future circumstances. Hence, the best option is to encourage diversity in the banking sector (e.g., Michie, 2011; Michie & Oughton, 2022).[3] In the words of Ayadi et al. (2010, p. vi), "in many respects it is the mix of different types of institutions that is important… as much (if not more so) than the merits of any particular ownership structure or business model."

Since the biodiversity argument in banking and, more broadly, the analysis of socio-economic diversity (e.g., Maignan et al., 2003) recalls insights from ecology, we follow other contributions (e.g., Baum et al., 2020; Kotz & Schäfer, 2018; Michie & Oughton, 2022) and borrow from ecological theories the diversity measures used in this paper. They are the Gini-Simpson index (Simpson, 1949) and, for robustness, the Shannon index (Shannon, 1948). In computing these measures, we rely on the institutional taxonomy of banks operating in the Italian system in the period under examination, 2009–2020. Indeed, as it reflects the dualism between large and small banks, this taxonomy allows us to catch banks' heterogeneity in terms of their business models and lending technologies – while accounting for the variety of ownership structures, governance mechanisms and objective functions characterizing the national banking sector.

We conduct our analysis at the Italian local credit market level, which, according to the National Competition Authority, roughly corresponds to the country's administrative provinces (NUTS-3 regions). To account for the role of local banking competition on new firms' formation, an issue that has been investigated in a considerable corpus of research (e.g., Black & Strahan, 2002; Wall, 2004; Bonaccorsi di Patti & Dell'Ariccia, 2004; Gagliardi, 2009; Rogers, 2012; Agostino & Trivieri, 2016), we employ a measure of credit market concentration. In doing so, however, we diverge from the existing research in that we aim to disentangle the *diversity effect* (our primary focus) from the *competition effect,* as they refer to different banking structural features. Indeed, as Baum et al. (2020, p. 5) claim: "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."

Our estimation results provide support to the biodiversity argument, as they suggest that institutional bank variety in local credit markets benefits new firms' formation. A direct policy implication of this finding is that authorities should implement regulations designed to preserve and promote diversity in the banking landscape. Furthermore, we find that the impact of banking diversity is sharper for new limited liability companies than for firms taking other legal forms (unincorporated partnerships, sole proprietors, and cooperatives). This finding is also relevant in terms of policy implication since, in the current Italian legislation, start-ups "of a high-technological-value" (Italian Ministry of Economic Development, 2015, p. 2) are required to assume the legal form of limited liability companies. Finally, we provide evidence that, during the initial phases of the COVID-19 crisis, institutional diversity in local credit markets might have mitigated the adverse effect of pandemic turmoil on firms' entry rates.

The remainder of the paper is organized as follows. The next section describes the indexes employed to measure banking diversity. Section 3 illustrates the econometric model, the identification strategy and the data used. Section 4 discusses the empirical results, and section 5 presents an extension of the analysis. Finally, section 6 provides concluding remarks.

2. Measuring banking diversity

Since the concept of *diversity* – seen in terms of different corporate forms or types across an industry or a market – resembles the notion of diversity among *species* in a population or an *ecosystem*, to gauge its measurement, scholars rely on indexes developed in the bio-ecological sciences (e.g., Baum et al., 2020; Costanzo et al., 2023; Kotz & Schäfer, 2018; Michie & Oughton, 2022).[4] Among these

[3] With specific regard to the role of financial systems' diversity on systemic stability, we refer to Haldane and May (2011), Goodhart and Wagner (2012) and NEF (2015).

[4] On this issue, see also Maignan et al. (2003). They provide an in-depth interdisciplinary comparison between bio-ecological and socio-economic diversity measures.

indexes, one of the most commonly employed is the Gini-Simpson index, the complement to the original Simpson formulation (Simpson, 1949). It is given by:

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

where, in our analysis, b_{ipt} is the proportion of branches of bank type *i*, in province *p*, at time *t*. On the interpretative ground, GINI-SIMPSON measures the probability that two branches, drawn randomly from the dataset, belong to different bank types (*K*). Therefore, the index takes its minimum if only one bank type operates in a given market, and its value increases as *K* becomes larger and the degree of equality in the distribution of branches among *K* increases.[5]

The *K* bank types we consider are the three categories of credit institutions characterizing the Italian banking system and the (branches of) foreign institutions.[6] The domestic categories include: 1) the corporation banks (*SpA*), consisting of for-profit commercial banks, typically large, multimarket, nonlocal institutions; 2) the *Banche di Credito Cooperativo* (or BCCs), generally small, single-market, local banks – with a specific characterization (in terms of ownership structure, corporate governance, statutory requirements and business objectives) that configure them as mutualistic, not-for-profit credit firms; 3) finally, the *Popolari* cooperatives represent an intermediate category between the previous two (e.g., Botta & Colombo, 2020). Indeed, these banks share some statutory requirements with the BCCs, such as the one-member/one-vote principle, limitations in shareholder participation, the necessity of board approval for the admission of new members and the mandatory provision to allocate a share of profits to legal reserves. However, some other aspects – both in terms of less stringent regulation (concerning, for instance, the expansion of their branch network and the possibility of operating with non-members) and in terms of corporate strategies, by which "they seek profit as much as the joint stock banks do" (Bongini & Ferri, 2008, p. 2) – make the *Popolari* cooperatives close to the model of corporation banks.[7]

Finally, it is worth underlining that – besides the considerations discussed in the previous section – there is at least another reason why the diversity indexes we employ should not be viewed as measures of bank competition. To compute GINI-SIMPSON and SHANNON, we resort to the number and the market shares of institutional bank categories rather than of individual banks so that, even if (1) and (2) were proxying for some kind of market competition, the latter would ultimately be among bank *types* – which is indeed the notion of banking diversity we intend to catch.

3. Empirical strategy

3.1. Model

We estimate the following model:

$$ENTRY_{pst} = \alpha + \beta_1 ZGINI_{p(t-1)} + \psi \boldsymbol{X}_{(t-1)} + \sum_s \gamma_s IND_s + \sum_t \varphi_t T_t + \epsilon_{pst} \tag{3}$$

where the dependent variable is the entry rate (ENTRY) of manufacturing firms in province *p*, industry *s* at time *t*, computed as the ratio of newly registered enterprises at time *t* over the stock of existing firms at time *t-1*. In Section 5, which extends our analysis, the dependent variable is ENTRYLL for limited liability companies and ENTRYOTH for firms in the legal form of unincorporated partnerships, sole proprietors and cooperatives. As in Agostino et al. (2020), we always use gross entry rates (controlling for firms' exit rates) rather than net entry rates. Indeed, employing a net measure means assuming that the same causal factors drive entries and exits. Moreover, since net entry rates hide information on the absolute values of the involved processes, the interpretation of the regression

[5] Another diversity index widely used in ecological models is the Shannon index (Shannon, 1948), given by:

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

As this index is mathematically quite close to GINI-SIMPSON, we expect – and indeed find – a high correlation between the two measures (0.985). Hence, we employ SHANNON for robustness only (see subsection 4.1).

[6] Bruno and Hauswald (2013) and Claessens and Van Horen (2014) extensively analyse the effects of foreign bank penetration on the development and efficiency of financial systems in their host countries. On the role of these banks in financing small firms, see also Clarke et al. (2001 and 2005) and Detragiache et al. (2008).

[7] Until the early '90s, the Italian banking system categorized the savings banks (*Casse di Risparmio)* as another specific institutional form of credit intermediaries. This bank category has progressively disappeared due to the profound changes in the national banking regulation beginning with the 1990 Amato-Carli law, which led – among other things – to the transformation of *Casse di Risparmio* into *SpA* banks (e.g., Ayadi et al., 2009). As noted by an anonymous referee, while some former saving banks merged and created large corporate entities, others remained faithful to their original "local" business model – and it would be interesting to include these latter explicitly in our analysis. Unfortunately, the data provided by the Italian Banking Association (ABI), employed to compute the diversity indexes (see sub-section 3.3), do not allow us to go beyond the classification of bank types discussed in this section. The same reason precludes us from identifying and treating the few ethical banks operating in Italy as a separate category.

Table 1
Description and summary statistics.

		Mean	Std. Dev.	Min	Max	Obs
ENTRY (a)	Entry rate: newly registered firms at time t over the stock of existing firms at time t-1 (provincial-sectoral level)	2.15	2.50	0	14.29	24,565
ENTRYLL (a)	Entry rate: newly registered limited liability (LL) firms at time t over the stock of existing LL firms at time t-1 (provincial-sectoral level)	1.26	2.33	0	16.67	24,338
ENTRYOTH (a)	Entry rate of firms others than the LL ones (OTH) at time t over the stock of existing OTH firms at time t-1 (provincial-sectoral level)	1.68	2.27	0	14.29	24,565
ZGINI	Standardized Gini-Simpson index (provincial level)	0.00	1.00	−2.78	1.81	28,261
HHID	Herfindahl–Hirschman Index on deposits (provincial level. See section 3)	0.15	0.06	0.04	0.47	28,261
BNKSIZE (a)	Share of corporation banks branches over total branches (provincial level)	69.27	16.54	9.30	100	28,261
BNKLNS (a)	Total bank loans to firms over total deposits (provincial level)	120.2	42.69	37.50	302.4	28,213
BRDENS (a)	Banks branches per 10,000 inhabitants (provincial level)	5.2	1.86	1.60	10.7	28,261
FDENS (b)	Number of registered firms per 10,000 inhabitants (provincial level)	102.0	40.76	44	384.9	28,261
FSIZE (b)	Number of employees in manufacturing firms (regional-sectoral level)	12.16	20.30	0	725.7	24,315
URATE (a)	Unemployment rate (provincial level)	10.60	5.45	2.10	31.46	28,213
EMPC (b)	Number of employees in manufacturing sectors per thousand inhabitants (regional-sectoral level)	27.54	33.06	0	338.6	24,638
WAGE (c)	Average wage in manufacturing sectors (regional-sectoral level)	24,627	9473	7742	53,210	23,900
VAPC	Per-capita value-added (provincial level)	23,028	6208	12,919	50,126	25,813
PRVSIZE	Provincial size: number of municipalities	4.09	0.73	1.79	5.75	28,261
POPD (b)	Population over provincial surface (in square km; provincial level)	272.8	384.9	38.34	2652.7	28,261
EXIT (a)	Exit rate: ceased firms at time t over the stock of existing firms at time t-1 (provincial-sectoral level)	4.59	3.53	0	20.0	24,565
Robustness						
VAG (a)	Value-added growth rate (provincial level)	0.91	2.49	−18.27	20.63	23,350
EXP (a)	Export over GDP (provincial level)	24.80	23.34	0.06	295.5	25,765
IQI	Institutional quality index (provincial level)	0.59	0.25	0.00	1.00	28,261
INFRA	Infrastructural endowment (regional level)[a]	0	1.88	−3.48	3.48	28,261
EDU (a)	Share population (25–64) with upper secondary, post-secondary and tertiary education (regional level)	59.27	6.77	43.00	71.80	28,261
HOUSEPR	House price index, annual averages (macro-regions level: North-West, North-East, Centre and Mezzogiorno)	106.3	8.65	95.20	128.8	28,261
HHHIL	Herfindahl–Hirschman Index on loans (provincial level. See section 3)	0.159	0.06	0.04	0.52	28,261
HHHIA	Herfindahl–Hirschman Index on bank assets (provincial level. See section 3)	0.164	0.06	0.03	0.49	28,261
RGDPPC (c)	Real per-capita gross domestic product (provincial level)	26,096	6921	14,538	55,821	25,355
PRATE (a)	Participation rate (provincial level)	64.50	8.24	40.61	76.78	28,213
ZSHANNON	Standardized Shannon index (provincial level)	0	1.00	−3.05	2.19	28,261

In percentage; (b) units; (c) euro. To rule out potential outliers, we trim the distribution of ENTRY, ENTRYLL, ENTRYOTH and EXIT, excluding the observations of the top and bottom one per cent.

[a] INFRA is obtained using a Principal Component Analysis on several highly correlated regional measures of infrastructural endowment, including the length of railway lines, roads and highways, the number of railway stations and airports and the tons of cargo moved by airports.

coefficients does not allow us to disentangle the impact of the explanatory variables on the two demographic dynamics (e.g., Fotopoulos & Spence, 1997).

On the right-hand side of (3), ZGINI is the standardized Gini-Simpson index,[8] **X** is a vector of control variables – borrowed primarily from the extant literature on business demography in the Italian provinces (e.g. Santarelli et al., 2009; Carree et al., 2011; Cainelli et al., 2014; Agostino et al., 2020) – 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.

The **X** vector includes the following variables: the Herfindahl–Hirschman Index on deposits (HHID) as a measure of local banking concentration;[9] the share of large banks branches over total branches to control for the average size of the credit institutions in the market (BNKSIZE); the amount of bank credit provided to firms over bank deposits (BNKLNS) as a proxy for financial conditions in the province (Agostino et al., 2020); the number of banks branches per 10,000 inhabitants (BRDENS), as a measure of provincial branch network density, to account for bank-firm proximity; the number of manufacturing firms per 10,000 inhabitants (FDENS) and their

[8] ZGINI follows a standard normal distribution (with mean $\mu = 0$ and standard deviation $\sigma = 1$) to facilitate the interpretation of the results.

[9] $HHID_p = \sum(ms_{ip})^2$, where $ms_{ip} = (D_{ip}/D_p)$ is the market share on deposits for each branch office of bank i in province p, and $D_p = \sum_i D_{ip}$. As 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 $D_{ip} = D_i{*}(BR_{ip}/BR_i)$, 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. We acknowledge 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 & Zaretsky, 2003; Berger et al., 2004). Nonetheless, as Petersen and Rajan (1995) argue, 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), as most likely is the case for nascent firms. We employ the same criterion above to compute the Herfindahl–Hirschman Index on loans (HHIL) and banks' total assets (HHIA), both measures used to perform robustness checks.

Table 2
Correlation matrix.

	ZGINI	HHID	BNKSIZE	BNKLNS	BRDENS	FDENS	FSIZE	URATE	EMPC	WAGE	VAPC	PRVSIZE	POPD	EXIT	VAG	EXP	IQI	INFRA	EDU	HOUSEPR	HHHIL	HHIA	RGDPPC	PRATE	ZSHANNON
ZGINI	1																								
HHID	−0.341	1																							
BNKSIZE	−0.845	0.160	1																						
BNKLNS	−0.014	−0.224	0.058	1																					
BRDENS	0.102	−0.091	−0.155	0.533	1																				
FDENS	0.006	−0.126	0.032	0.329	0.342	1																			
FSIZE	0.042	−0.035	−0.036	0.033	0.130	0.070	1																		
URATE	−0.114	0.082	0.137	−0.392	−0.754	−0.400	−0.154	1																	
EMPC	0.062	−0.055	−0.052	0.143	0.307	0.177	0.108	−0.311	1																
WAGE	0.111	−0.048	−0.115	0.056	0.229	0.095	0.517	−0.290	0.047	1															
VAPC	0.154	−0.230	−0.138	0.345	0.625	0.306	0.138	−0.744	0.257	0.300	1														
PRVSIZE	0.045	−0.027	−0.082	−0.069	0.090	−0.091	0.020	−0.118	0.016	0.086	0.172	1													
POPD	0.078	−0.183	0.067	0.098	−0.126	0.075	0.007	−0.011	0.042	0.072	0.265	0.031	1												
EXIT	−0.006	−0.038	0.020	0.046	0.049	0.023	−0.174	−0.059	0.074	−0.227	0.045	−0.006	0.003	1											
VAG	0.016	−0.080	−0.011	0.068	0.105	0.074	0.029	−0.180	0.058	0.079	0.210	0.025	0.045	−0.018	1										
EXP	0.137	0.011	−0.118	0.034	0.200	0.162	0.050	−0.188	0.118	0.103	0.214	0.019	−0.021	−0.012	0.078	1									
IQI	0.187	−0.155	−0.198	0.320	0.784	0.392	0.164	−0.817	0.344	0.308	0.771	0.100	0.074	0.050	0.144	0.275	1								
INFRA	0.178	0.037	−0.123	0.215	0.135	0.070	0.030	−0.167	0.115	0.180	0.199	0.205	0.220	0.025	0.040	0.166	0.125	1							
EDU	0.165	−0.135	−0.188	0.033	0.484	0.188	0.106	−0.612	0.209	0.295	0.638	0.056	0.016	0.014	0.115	0.204	0.643	0.015	1						
HOUSEPR	−0.075	−0.068	0.104	0.608	0.396	0.201	0.015	−0.281	0.087	−0.050	0.062	−0.017	0.001	0.071	−0.072	−0.034	0.134	0.046	−0.158	1					
HHHIL	−0.310	0.978	0.171	−0.246	−0.112	−0.134	−0.034	0.098	−0.064	−0.048	−0.225	−0.012	−0.157	−0.031	−0.092	0.001	−0.159	0.033	−0.130	−0.083	1				
HHIA	−0.297	0.969	0.167	−0.221	−0.102	−0.143	−0.032	0.087	−0.057	−0.041	−0.199	−0.011	−0.131	−0.025	−0.091	0.014	−0.148	0.069	−0.126	−0.055	0.981	1			
RGDPPC	0.129	−0.232	−0.107	0.411	0.661	0.322	0.138	−0.767	0.266	0.291	0.992	0.162	0.263	0.051	0.223	0.213	0.774	0.203	0.609	0.150	−0.229	−0.200	1		
PRATE	0.075	−0.064	−0.094	0.296	0.751	0.408	0.153	−0.788	0.320	0.319	0.811	0.062	0.032	0.039	0.168	0.280	0.879	0.198	0.754	0.049	−0.071	−0.066	0.805	1	
ZSHANNON	0.985	−0.376	−0.796	0.009	0.105	0.016	0.044	−0.140	0.069	0.124	0.194	0.064	0.133	−0.002	0.020	0.131	0.215	0.196	0.185	−0.060	−0.340	−0.322	0.170	0.099	1

For the description of the variables, see Table 1.

average size (FSIZE), as proxies of industrial structure; the unemployment rate (URATE), the number of employees in manufacturing sectors per thousand inhabitants (EMPC), and the average sectorial wages (WAGE), to consider local labor market conditions (Santarelli et al., 2009);[10] the log of per-capita value-added (VAPC), the number of municipalities (PRVSIZE) and the population density (population per square km, POPD), to control for provincial differences in the level of development and size (Carree et al., 2011); and, finally, the firms' exit rate (EXIT) to account for firms' turnover and "turbulence" phenomena (e.g., Baptista & Karaoz, 2011). All the explanatory variables are lagged once to avoid simultaneity bias.

A more detailed description of all the variables employed in our estimations and their main statistics are shown in Table 1. Table 2 provides a correlation matrix.

3.2. Identification

We estimate Equation (3) using a two-limit (0,100) Tobit model, given that ENTRY is restricted to the zero value for a nontrivial amount of observations (and not as a result of truncation). Moreover, considering that our dependent variable is a proportion, we run a Fractional Probit regression model to overcome the drawbacks of linear models for fractional data (e.g., Papke & Wooldridge, 1996, 2008). In addition, we estimate a random effect Tobit model to control unobserved time-invariant heterogeneity at the sectoral-provincial level. Although this estimator does not account for the potential correlation between the regressors and the unobserved specific effects, we do not employ a fixed-effects technique because the latter might entail an incidental parameter problem in limited dependent variable models, leading to inconsistent estimations (e.g., Wooldridge, 2002).

Furthermore, we estimate an instrumental variables Tobit model to address endogeneity concerns related to unobservable factors driving firms' entry and local banking diversity, as well as reverse causality issues (firms could self-select into credit markets characterized by a higher banking diversity). To retrieve valid instruments for the key variable (see sub-section 4.1), following Guiso et al. (2004 and 2006), we argue that the territorial structure of the Italian banking system in 1936 – when, in response to the crisis of 1930–1933, strict banking regulations were introduced (and 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" (Guiso et al., 2004, p. 946). Moreover, the 1936 regulation was not driven by different regional needs, "but it was random" (p. 943). By relying on these considerations, the geographical distribution of banks and branches in 1936 – whilst plausibly exogenous to the entrepreneurial dynamics in recent years (Guiso et al., 2004) – should be correlated with the current banking landscape. Yet, on this point, a note of caution is in order. The Italian banking system has indeed undergone a considerable structural transformation process, most notably during the 1990s/early 2000s and, to a lesser extent, in the last decade (e.g., Del Prete et al., 2022, p. 1382), which has undoubtedly changed its previous institutional physiognomy. Bearing this in mind, we acknowledge that the temporal external validity of our instruments could indeed be limited.

We also recognize that potential spillover effects might be at work across provinces. Indeed, bank branch distribution and firms' entry rates in neighbouring local markets might affect each other. Further, the impact of bank diversity on new firms' formation in a given province might affect the rate of nascent firms in the adjacent ones, as business relationships could link neighbouring local economies. To account for such effects, spatial econometrics methodologies are commonly employed. In our case, however – as some variables, including the dependent one, are defined at the provincial-sectoral level – resorting to such techniques is problematic (e.g., Gibbons & Overman, 2012; McMillen, 2010). Indeed, we should collapse the sample at the territorial dimension, thus reducing its size from around 20,000 to approximately 1000 observations, which would pose severe concerns about the statistical reliability of the estimation results.

Nonetheless, to get some insights into the issue, we have estimated a conventional SLX, spatially lagged X, model (e.g., Halleck Vega & Elhorst, 2015). The outcome of this exercise, reported in Table A1 in the Appendix,[11] indicates that the spillover effects of banking diversity (W*ZGINI) on firms' entry rates are not statistically significant in our analysis. Further, looking at the Wald statistics, the null hypothesis of the absence of spatial interaction effects cannot be rejected.

In addition, to explore the presence of dependence across provinces while preserving the original unit of analysis and maintaining a sufficiently large number of observations for each sector, we performed the Pesaran (2021) test for panel data, considering one industry at a time. The test results, shown in Table A2 (in the Appendix), provide evidence supporting the estimators we adopt. Indeed, for most sectors (65% of the cases), the null hypothesis of independence across provinces cannot be rejected.

3.3. Data

Our data are obtained from several sources. Information on bank branches to compute the local banking diversity indexes and the measures of credit market concentration comes from the Italian Banking Association (ABI) and the Bank of Italy-Statistical Database (BDS). Data on firms' demography are retrieved from the *Movimprese-InfoCamere* dataset, and the information on provincial and regional features employed as control variables (except bank deposits and loans, extracted from BDS) is drawn from the Italian National Institute of Statistics (ISTAT) and EUROSTAT. All these data are at the annual frequency.

The *Movimprese* dataset, held by the information service consortium of the Italian Chambers of Commerce, provided us with the

[10] EMPC and WAGE are available for 2009-18 only. Thus, we impute their values from 2018 to 2019.

[11] Columns 1 and 2 of this table show the SLX estimation results when the model comprises the spatial lag term of ZGINI only and the spatial lag term of all the explicative variables in the **X** vector of Equation (3), respectively.

flows of newly registered enterprises and of those exiting the market – as well as the stocks of all recorded firms – for 105 Italian provinces (out of the current total of 107)[12] and 24 manufacturing sectors (classified following the NACE Rev.1 system from 1995 to 2008, and the NACE Rev. 2 taxonomy from 2009 forward).[13] By legal status, firms are grouped into limited liability companies, unincorporated partnerships, sole proprietors, and other forms of ownership (mainly cooperatives).

Given the aggregation level of the data employed, our analysis does not consider micro-level determinants of firms' entry rates, such as specific characteristics of enterprises (age, size, etc.) and socio-demographic aspects of entrepreneurs (e.g., sex, age, education, etc.). We acknowledge this lack as a limitation of the present study.

4. Results

Column 1 of Table 3 shows the pooled Tobit estimation results of our benchmark model (Equation (3)). The estimated coefficient of ZGINI displays a positive sign and appears statistically significant at the conventional level. In terms of numerical interpretation, we find that one standard deviation increase in ZGINI is associated with an increase in the latent outcome variable – the propensity of new firms entering the market – of around 5% (a rise of 0.1112 percentage points over a baseline of 2.15).[14] This finding suggests that the coexistence of different institutional bank types in local credit markets may be paramount in facilitating new firms' formation, thus supporting the biodiversity argument discussed in Section 1. Far from questioning the role of each bank model, our results align with the view that, beyond the strengths and weaknesses of any of these models, institutional variety in the banking landscape matters in financing the real economy. Therefore, to borrow the words of Ferri (2010), a policy implication of our analysis is that "authorities must be aware that any regulation – e.g., levelling the playing field – should not damage the biodiversity of banking (p. 3)".

Turning now to the results of the control variables – and focusing first on the proxies for credit market characteristics – we find that the estimated parameters of HHID, BNKSIZE and BRDENS are all statistically significant. The negative coefficient of the former appears to be in line with the findings of other studies, which show that an increase in bank market power would be detrimental to new business formation. (e.g., Agostino & Trivieri, 2016; Black & Strahan, 2002; Cetorelli & Strahan, 2006). The sign of the estimated parameter of BNKSIZE suggests that a larger average bank size in the market does not harm firms' creation, thus aligning with the indications of those contributions disputing that small banks (still) have a comparative advantage in serving informationally opaque firms (Berger et al., 2005; Berger & Udell, 2006). Lastly, the positive sign of the BRDENS coefficient confirms the relevance of bank-firm proximity on lenders' ability to collect qualitative information and, in this way, on loan supply (e.g., Agarwal & Hauswald, 2010; Brevoort & Hannan, 2006).

Finally, considering the other statistically significant control variables, the estimated parameters of FDENS, POPD, and EXIT confirm the figures of Agostino et al. (2020) – and the results of the variables accounting for local labour market conditions (EMPC and WAGE) appear in line with the findings of Santarelli et al. (2009).

4.1. Robustness checks

Columns 2–11 of Table 3 report the output of several robustness checks performed by changing the benchmark specification by adding or replacing control variables. More specifically, columns 2 to 4 show the estimation results when the econometric model is augmented with other potential provincial controls, such as the value-added growth rate (VAGR), the ratio of export to gross domestic product (EXP) and an institutional quality index (IQI), provided by Nifo and Vecchione (2014). The figures in columns 5 to 7 are obtained when Equation (3) includes some proxies at the regional level: the share of the population (25–64 years) with upper secondary, post-secondary and tertiary education (EDU), an infrastructural endowment indicator (INFRA),[15] and a house price index (HOUSEPR).[16] Columns 8 and 9 display the estimation results using the Herfindahl-Hirschman index computed on loans (HHIL) and assets (HHIA) as alternative measures of credit market concentration.[17] Finally, in columns 10–11, we substitute the proxies for local

[12] No data is available for Barletta-Andria-Trani (a province in the Puglia region) and Sud-Sardegna (in Sardinia).

[13] Since sectorial data are (always) available at the sectoral 2-digit level, we were precluded from obtaining an exact match between the two periods, which is why the first year of our analysis is 2009.

[14] In the limited dependent-variable model we adopt, the estimated coefficients gauge the (linear) marginal effect of each regressor on the *latent* (unobservable) outcome variable.

[15] INFRA is obtained using a Principal Component Analysis on several highly correlated regional measures of infrastructural endowment (over the period 2009–2020), including the length of railway lines, roads and highways, the number of railway stations and airports and the tons of cargo moved by airports.

[16] Available at the macro-regions level: North-West, North-East, Centre, and *Mezzogiorno* (comprising the southern regions and the two biggest islands, Sicily and Sardinia).

[17] To allow a direct comparison between the estimated parameters of the diversity index and the measure of banking concentration, Table A3 (in the Appendix) shows the estimation results using GINI and HHID/L/A in the standardized form, together with the outcomes of F-tests performed on the coefficients of the same variables. In our view, these results provide evidence in line with the argument of Baum et al. (2020) that *diversity* and *competition* are distinctive dimensions related to bank structural characteristics.

Table 3
Estimation results: dependent variable ENTRY.

	1	2	3	4	5	6	7	8	9	10	11
	Benchmark	Adding VAG	Adding EXP	Adding IQI	Adding INFRA	Adding EDU	Adding HOUSEPR	HHIL instead of HHID	HHIA instead of HHID	RGDPPC intead of VAPC	PRATE instead of URATE
ZGINI	0.1112**	0.1077**	0.1164**	0.1114**	0.1112**	0.1187**	0.1145**	0.1356***	0.1351***	0.1027**	0.1111**
	0.0340	*0.0400*	*0.0270*	*0.0330*	*0.0340*	*0.0250*	*0.0290*	*0.0080*	*0.0080*	*0.0490*	*0.0340*
HHID	−1.7235***	−1.7310***	−1.7259***	−1.7239***	−1.7196***	−1.6430***	−1.7060***			−1.9098***	−1.7214***
	0.0010	*0.0010*	*0.0010*	*0.0010*	*0.0010*	*0.0020*	*0.0010*			*0.0000*	*0.0010*
BNKSIZE	0.0072**	0.0070**	0.0073**	0.0071**	0.0072**	0.0072**	0.0070**	0.0083***	0.0084***	0.0069**	0.0072**
	0.0240	*0.0260*	*0.0210*	*0.0250*	*0.0240*	*0.0230*	*0.0260*	*0.0080*	*0.0080*	*0.0300*	*0.0240*
BNKLNS	0.0006	0.0007	0.0006	0.0006	0.0006	0.0008	0.0008	0.0007	0.0007	0.0006	0.0006
	0.4710	*0.4380*	*0.4850*	*0.4650*	*0.4670*	*0.3780*	*0.3790*	*0.4390*	*0.4310*	*0.4630*	*0.4810*
BRDENS	1.0832***	1.0937***	1.0944***	1.0834***	1.0836***	1.0775***	1.0838***	1.0939***	1.1079***	1.0444***	1.0878***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
FDENS	0.6643***	0.6581***	0.6732***	0.6627***	0.6646***	0.6657***	0.6667***	0.6717***	0.6713***	0.6615***	0.6646***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
FSIZE	−0.1272	−0.1263	−0.1270	−0.1272	−0.1273	−0.1274	−0.1274	−0.1264	−0.1267	−0.0706	−0.1270
	0.2150	*0.2180*	*0.2160*	*0.2150*	*0.2150*	*0.2150*	*0.2150*	*0.2180*	*0.2170*	*0.5000*	*0.2160*
URATE	−0.0021	−0.0030	−0.0009	−0.0025	−0.0021	−0.0005	0.0000	−0.0018	−0.0013	−0.0028	
	0.8310	*0.7590*	*0.9260*	*0.8020*	*0.8320*	*0.9560*	*0.9990*	*0.8500*	*0.8970*	*0.7740*	
EMPC	0.2281***	0.2278***	0.2282***	0.2281***	0.2281***	0.2274***	0.2285***	0.2276***	0.2278***	0.2122***	0.2280***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
WAGE	−0.5932***	−0.5921***	−0.5946***	−0.5934***	−0.5933***	−0.5941***	−0.6016***	−0.5918***	−0.5928***	−0.6063***	−0.5926***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
VAPC	0.0738	0.0136	0.0843	0.0826	0.0746	0.0670	0.0733	0.0985	0.1161		0.0761
	0.7090	*0.9460*	*0.6700*	*0.6780*	*0.7070*	*0.7350*	*0.7110*	*0.6180*	*0.5560*		*0.7090*
PRVSIZE	−0.0810	−0.0794	−0.0862	−0.0806	−0.0811	−0.0783	−0.0811	−0.0743	−0.0769	−0.0870	−0.0820
	0.3020	*0.3110*	*0.2740*	*0.3050*	*0.3010*	*0.3180*	*0.3010*	*0.3430*	*0.3260*	*0.2650*	*0.2930*
POPD	0.2012***	0.2051***	0.1979***	0.2019***	0.2011***	0.2020***	0.2000***	0.2133***	0.2149***	0.1874***	0.2001***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
EXIT	0.0770***	0.0771***	0.0769***	0.0770***	0.0770***	0.0768***	0.0768***	0.0772***	0.0773***	0.0812***	0.0770***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
VAG		0.0169*									
		0.0770									
EXP			−0.0009								
			0.4050								
IQI				−0.0601							
				0.8290							
INFRA					0.0189						
					0.8930						
EDU						0.0233					
						0.2950					
HOUSEPR							−0.0096				
							0.1580				

	1	2	3	4	5	6	7	8	9	10	11
	Benchmark	Adding VAG	Adding EXP	Adding IQI	Adding INFRA	Adding EDU	Adding HOUSEPR	HHIL instead of HHID	HHIA instead of HHID	RGDPPC intead of VAPC	PRATE instead of URATE
HHIL								−1.1760**			
								0.0140			
HHIA									−1.1517**		
									0.0120		
RGDPPC										0.0936	
										0.6360	
PRATE											0.0014
											0.8740
Observations	20,654	20,654	20,654	20,654	20,654	20,654	20,654	20,654	20,654	20,309	20,654
Left-censored	6508	6508	6508	6508	6508	6508	6508	6508	6508	6031	6508
Model test	199.6	197.0	196.9	196.7	196.6	195.9	195.2	200.4	200.1	200.0	199.7
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Log pseudolikelihood	−37586.4	−37584.8	−37586.0	−37586.4	−37586.4	−37585.8	−37585.4	−37589.1	−37589.0	−37025.8	−37586.4

For the description of the variables, see Table 1. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The p-values of the tests are in italics. The standard errors (not reported) are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias. The variables BRDENS, FDENS, FSIZE, EMPC, WAGE, VAPC, PRVSIZE, POPD 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 the joint significance of all explanatory variables.

Table 4
Other robustness checks.

	1	2	3	4	5	6
	Average marginal effects		ZSHANNON	FRACREG	XTTOBIT	IVTOBIT
	E(y|x)	E(y|y > 0, x)				
ZGINI	0.0744**	0.0639**		0.0009***	0.1028*	0.8456***
	0.0340	*0.0260*		*0.0080*	*0.0820*	*0.0000*
ZSHANNON			0.0837**			
			0.0390			
HHID	−1.1534***	−0.9911***	−1.7852***	−0.0078**	−1.5059***	0.2072
	0.0010	*0.0010*	*0.0010*	*0.0190*	*0.0070*	*0.7880*
BNKSIZE	0.0048**	0.0041**	0.0047**	0.0001***	0.0079**	0.0410***
	0.0240	*0.0170*	*0.0460*	*0.0100*	*0.0250*	*0.0000*
BNKLNS	0.0004	0.0004	0.0006	0.0000	0.0007	0.0016*
	0.4710	*0.4840*	*0.4670*	*0.8930*	*0.4950*	*0.0850*
BRDENS	0.7249***	0.6229***	1.0568***	0.0072***	0.9586***	0.2713
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0070*	*0.4300*
FDENS	0.4446***	0.3820***	0.6688***	0.0034***	0.6532***	0.7677***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
FSIZE	−0.0851	−0.0732	−0.1268	0.0017**	−0.0925	−1.0051***
	0.2150	*0.1070*	*0.2170*	*0.0120*	*0.3800*	*0.0000*
URATE	−0.0014	−0.0012	−0.0028	0.0000	−0.0060	0.0030
	0.8310	*0.8230*	*0.7710*	*0.7410*	*0.5550*	*0.8020*
EMPC	0.1527***	0.1312***	0.2283***	−0.0004	0.2269***	1.0780***
	0.0000	*0.0000*	*0.0000*	*0.2040*	*0.0010*	*0.0000*
WAGE	−0.3970***	−0.3411***	−0.5948***	−0.0032***	−0.5314***	−0.9228***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0010*	*0.0000*
VAPC	0.0494	0.0425	0.0609	−0.0017	0.1674	0.0248
	0.7090	*0.7210*	*0.7580*	*0.1700*	*0.5540*	*0.9170*
PRVSIZE	−0.0542	−0.0466	−0.0768	−0.0021***	−0.0124	0.0069
	0.3020	*0.2510*	*0.3270*	*0.0000*	*0.8990*	*0.9370*
POPD	0.1346***	0.1157***	0.2027***	0.0002	0.2477***	0.0951*
	0.0000	*0.0000*	*0.0000*	*0.5430*	*0.0000*	*0.0960*
EXIT	0.0515***	0.0443***	0.0768***	0.0005***	0.0405***	0.1230***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
First-Stage IV						
BR36						0.1014***
						0.0000
SBR36BIG						0.0071***
						0.0000
SBR36BIG2						−0.0001***
						0.0000
SBR36CP						0.0068***
						0.0000
SBR36CP2						−0.0001***
						0.0000
Observations	20,654	20,654	20,654	20,654	20,654	18,046
Left-censored			6508		6508	5469
Model test	199.6	199.6	199.0	13173.1	5327.1	6140.4
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Log pseudolikelihood	−37586.4	−37586.4	−37586.6	−2072.8	−37266.3	
F-test instrm						285.4
P-value						*0.0000*
Wald test of exogeneity						14.6
						0.0001
Test of overid. restrictions:						3.9
(Amemiya-Lee-Newey chi-sq)						*0.4190*

For the description of the variables, see Table 1. The dependent variable is ENTRY (ENTRY/100 in column 4). Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The p-values of the tests are in italics. The standard errors (not reported) are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias. The variables BRDENS, FDENS, FSIZE, EMPC, WAGE, VAPC, PRVSIZE and POPD are in log terms. Year, sectoral and regional dummies are always included but not reported. Column 1 (2) shows the average marginal effects of the covariates on the unconditional (conditional) expected value of y, the observed outcome of ENTRY. The instrumental variables used in the IVTOBIT estimation (column 6) are the log of provincial banking branches in 1936 (BR36), the shares of branches owned in 1936 by the biggest banks (SBR36BIG) and cooperative banks (SBR36CP), the squares of SBR36BIG and SBR36CP. The null hypothesis of the Wald test of exogeneity is that the key regressor (ZGINI) is exogenous, while the null hypothesis of the Amemiya-Lee-Newey test is that all the instruments are exogenous. The model test in columns 1–3 (columns 4–6) is the F-test (Wald-Chi2 test) of the joint significance of all explanatory variables.

economic conditions: the real GDP per capita (RGDPPC) and the participation rate (PART) replace VAPC and URATE, respectively. All these sensitivity checks leave our results unchanged.[18]

Another set of robustness checks, which fully support our main finding, is reported in Table 4. The first two columns show the results obtained when computing the marginal effects of the covariates on the unconditional and conditional expected value of the observed outcome of ENTRY, respectively[19] – whilst, in column 3, we change the key regressor, replacing ZGINI with the standardized Shannon index (ZSHANNON).[20] Column 4 displays the figures attained by adopting the Fractional Probit estimator, and column 5 shows the results using a random-effects Tobit model. Finally, column 6 shows the estimates obtained when running an IV Tobit technique to deal with the endogeneity issue of our key regressor. As discussed above, to retrieve the instrumental variables (IVs), we rely on the strategy proposed by Guiso et al. (2004 and 2006) and look at the structural and territorial configurations of the Italian banking system as determined by the strict banking regulation reform in the '30s in response to the Great Depression. Following this approach, the IVs for which the null hypothesis of the Amemiya-Lee-Newey overidentifying restrictions test cannot be rejected are given by: the (the log of) provincial bank branches in 1936 (BR36), the shares of branches owned in 1936 by the biggest banks (SBR36BIG) and cooperative credit institutions (SBR36CP), and the squares of SBR36BIG and SBR36CP.[21]

5. Extending the analysis

This section extends our analysis in two directions. First, to provide some insights into the role of bank diversity with respect to the formation of innovative start-ups, we split the sample, separating the limited liability companies from the firms with other legal forms.[22] Agostino et al. (2020) suggest the rationale for doing so, pointing out that, since 2009, new enterprises of "high technological value" have been required to assume the legal form of limited liability companies.

The outcome of this econometric exercise, reported in Table 5, indicates that the positive impact of banking diversity on entry rates is much higher for the limited liability firms than for the others, regardless of the estimator employed. Although this analysis would require more granular data, the empirical evidence it provides would suggest that preserving and encouraging the variety of bank models in local credit markets could largely favour the formation of new innovative enterprises.

The second extension of our analysis aims to assess to what extent bank diversity might have affected new firms' formation during the first year of the COVID-19 pandemic. To do so, we insert in Equation (3) the dummy COVID – taking the value of 1 for the year 2020, the only pandemic period available in our dataset[23] – and the interaction term (INTEG) between ZGINI and COVID. Table 6 provides the outcome of these additional regressions. Looking at column 1, whose results are attained when ENTRY is the dependent variable, the parameters of ZGINI and INTEG display positive signs, and the estimated coefficient of COVID is negative and statistically significant. Moreover, the marginal effects of ZGINI + INTEG,[24] computed and tested using the approach of Brambor et al. (2006), also appear statistically significant, according to the t-tests reported in the final rows of Table 6.

Even though less sharp in columns 2 and 3, such a picture suggests that the favourable effect of local banking diversity on firms' entry rates would have been even sturdier during the initial phases of the pandemic crisis. This finding further supports the biodiversity argument proposed in the literature, as it corroborates the view that institutional pluralism in the banking landscape – preventing the economy from depending on a single bank model, which might not be best suited to all market circumstances (Llewellyn, 2009) – may results in a valuable asset in times of great turmoil and uncertainty.

In concluding this section, we acknowledge that the lack of data to account for the unprecedented policy measures most European governments have launched in the wake of the COVID-19 outbreak – including the public loan guarantee program (e.g., Cascarino et al., 2022, p. 1369) – could have biased the estimation figures reported in Table 6. Therefore, we invite the reader to consider these results as the outcome of an exploratory analysis, which we intend to deepen in future research.

[18] As argued by an anonymous reviewer, our results could be a function of the low interest rates in the period we investigate. While acknowledging this concern, we cannot provide a sensitivity check that accounts for this variable, as data on interest rates at the provincial level are not publicly available. On the other hand, following another suggestion of the same referee, we ran several regressions (using the benchmark specification) by dropping provinces one by one to inspect whether a small number of them drives our results. The outcome of this exercise, not reported to avoid cluttering, shows that the main findings of our analysis are qualitatively confirmed, up to a reduction of about 55% of the sample size.

[19] Let's *enter* the observed outcome of ENTRY, $E(enter|\boldsymbol{x})$ is the unconditional expectation and $E(enter|enter>0, \boldsymbol{x})$ the conditional expectation. The marginal effects of ZGINI, computed following Wooldridge (2002) and using the STATA *margins* command, indicate that the unconditional (conditional) expected value of observed firms' entry rates increases by almost 3.5% (3%) per one standard deviation increase in the key regressor.

[20] When doing so, one standard deviation increase in ZSHANNON is associated with a rise of almost 3.9% in the unobservable latent entry rate.

[21] The first-stage results, reported in column 5 of Table 4 and columns 4 and 8 of Table 5, indicate that our IVs are correlated to ZGINI.

[22] When estimating the first (the second) subsample, the dependent variable is ENTRYLL (ENTROTH). See Table 1 for the description of these variables.

[23] To avoid perfect collinearity, we omit the year 2020 from the set of temporal dummies (the baseline year is 2019).

[24] In our econometric framework, this marginal effect gauges the estimated impact of the diversity index on the propensity of new firms' formation during the initial phase of the COVID-19 crisis.

Table 5
Estimation results: dependent variable ENTRYLL and ENTRYOTH.

	1	2	3	4	5	6	7	8
	ENTRYLL				ENTRYOTH			
	Benchmark	FRACREG	XTTOBIT	IVTOBIT	Benchmark	FRACREG	XTTOBIT	IVTOBIT
ZGINI	0.2253**	0.0009**	0.2077*	1.1222***	0.0522	0.0004*	0.0430	0.8516***
	0.0340	*0.0300*	*0.0530*	*0.0000*	*0.3010*	*0.0910*	*0.4460*	*0.0000*
HHID	−0.6065	0.0012	−0.1938	1.3772	−1.8651***	−0.0075***	−1.7147***	0.2980
	0.5300	*0.7640*	*0.8480*	*0.2760*	*0.0000*	*0.0030*	*0.0010*	*0.6910*
BNKSIZE	0.0139**	0.0001***	0.0153**	0.0452***	0.0056*	0.0000**	0.0058*	0.0441***
	0.0280	*0.0060*	*0.0170*	*0.0020*	*0.0690*	*0.0300*	*0.0830*	*0.0000*
BNKLNS	0.0047***	0.0000*	0.0055***	0.0023	0.0002	0.0000	−0.0002	0.0017*
	0.0040	*0.0780*	*0.0030*	*0.1210*	*0.8210*	*0.5010*	*0.8710*	*0.0570*
BRDENS	1.6765***	0.0059***	1.7186***	0.6756	0.7514***	0.0042***	0.6363*	−0.0721
	0.0000	*0.0010*	*0.0030*	*0.2430*	*0.0030*	*0.0010*	*0.0600*	*0.8250*
FDENS	1.2592***	0.0024***	1.3573***	1.4326***	0.4926***	0.0019***	0.4782***	0.5421***
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
FSIZE	−0.9075***	−0.0009	−1.0026***	−1.2985***	−0.1757*	0.0012**	−0.1419	−1.0350***
	0.0000	*0.1940*	*0.0000*	*0.0000*	*0.0850*	*0.0360*	*0.1740*	*0.0000*
URATE	0.0470**	0.0001	0.0406**	0.0359**	−0.0127	−0.0001	−0.0141	−0.0046
	0.0120	*0.1530*	*0.0300*	*0.0440*	*0.1840*	*0.1680*	*0.1490*	*0.6870*
EMPC	0.9363***	0.0005	1.0122***	1.3233***	0.1959***	−0.0006**	0.1729***	1.0137***
	0.0000	*0.1530*	*0.0000*	*0.0000*	*0.0000*	*0.0260*	*0.0080*	*0.0000*
WAGE	−0.0512	0.0000	−0.0646	0.2371	−0.5412***	−0.0021***	−0.4201***	−1.0662***
	0.8490	*0.9890*	*0.8220*	*0.2750*	*0.0000*	*0.0040*	*0.0070*	*0.0000*
VAPC	2.3165***	0.0024*	2.2599***	1.2960***	−0.5469***	−0.0049***	−0.3735	−0.4423*
	0.0000	*0.0960*	*0.0000*	*0.0000*	*0.0040*	*0.0000*	*0.1660*	*0.0550*
PRVSIZE	0.2598*	−0.0018***	0.3190**	0.3108**	0.0313	−0.0013***	0.0781	0.1727**
	0.0720	*0.0020*	*0.0490*	*0.0350*	*0.6770*	*0.0010*	*0.4050*	*0.0420*
POPD	0.3990***	−0.0007**	0.4720***	0.5233***	0.2117***	0.0001	0.2370***	0.0701
	0.0000	*0.0270*	*0.0000*	*0.0000*	*0.0000*	*0.8120*	*0.0000*	*0.1950*
EXIT	0.0208	0.0001*	0.0046	0.0471***	0.0779***	0.0004***	0.0453***	0.1158***
	0.1720	*0.0660*	*0.7230*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
ENTRYOTH	0.0784***	0.0004***	0.0631***	0.2030***				
	0.0020	*0.0000*	*0.0040*	*0.0000*				
ENTRYSC					0.0325***	0.0001***	0.0201**	0.0974***
					0.0010	*0.0060*	*0.0110*	*0.0000*
First-Stage IV								
BR36				0.0742***				0.0735***
				0.0000				*0.0000*
SBR36BIG				0.0099***				0.0117***
				0.0000				*0.0000*
SBR36BIG2				−0.0001***				−0.0001***
				0.0000				*0.0000*
SBR36CP				0.0067***				0.0070***
				0.0000				*0.0000*
SBR36CP2				−0.0001***				−0.0001***
				0.0000				*0.0000*
Observations	20,553	20,553	20,553	17,971	20,554	20,554	20,554	17,972
Left-censored	11,846		11,846	10,092	7933		7933	6766
Model test	79.23	2663.7	2263.3	2646.3	191.22	14234.1	5936.8	7259.3
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Log pseudolikelihood	−30376.2	−1386.5	−30259.8		−33094.0	−1652.3	−32777.4	
F-test (instruments)				275.13				289.80
				0.0000				*0.0000*
Wald test of exogeneity				11.52				20.00
				0.0007				*0.0000*
Test of overid. restrictions: (Amemiya-Lee-Newey chi-sq)				7.37				5.557
				0.1176				*0.2347*

For the description of the variables, see Table 1. The dependent variable is ENTRYLL/100 in column 2 and ENTRYOTH/100 in column 6. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The p-values of the tests are in italics. The standard errors (not reported) are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias. The variables BRDENS, FDENS, FSIZE, EMPC, WAGE, VAPC, PRVSIZE and POPD are in log terms. Year, sectoral and regional dummies are always included but not reported. The instrumental variables used in the IVTOBIT estimation (columns 4 and 8) are the log of provincial banking branches in 1936 (BR36), the shares of branches owned in 1936 by the biggest banks (SBR36BIG) and cooperative banks (SBR36CP), the squares of SBR36BIG and SBR36CP. The null hypothesis of the Wald test of exogeneity is that the key regressor (ZGINI) is exogenous, while the null hypothesis of the Amemiya-Lee-Newey test is that all the instruments are exogenous. The model test in columns 1 and 5 (columns 2–4 and 6–8) is the F-test (Wald-Chi2 test) of the joint significance of all explanatory variables.

Table 6
COVID-19 pandemic crisis.

	1	2	3
	ENTRY	ENTRYLL	ENTRYOTH
ZGINI	0.1050**	0.2188**	0.0477
	0.0460	*0.0390*	*0.3460*
COVID (2020 = 1)	−0.5135***	−0.2433	−0.5354***
	0.0000	*0.1650*	*0.0000*
INTEG	0.0762	0.0874	0.0546
	0.2500	*0.5440*	*0.3760*
HHID	−1.7183***	−0.6010	−1.8610***
	0.0010	*0.5340*	*0.0000*
BNKSIZE	0.0074**	0.0142**	0.0058*
	0.0200	*0.0280*	*0.0620*
BNKLNS	0.0007	0.0047***	0.0002
	0.4270	*0.0040*	*0.7770*
BRDENS	1.0747***	1.6676***	0.7452***
	0.0000	*0.0010*	*0.0030*
FDENS	0.6651***	1.2601***	0.4931***
	0.0000	*0.0000*	*0.0000*
FSIZE	−0.1273	−0.9077***	−0.1756*
	0.2150	*0.0000*	*0.0850*
URATE	−0.0022	0.0469**	−0.0127
	0.8240	*0.0120*	*0.1810*
EMPC	0.2278***	0.9361***	0.1956***
	0.0000	*0.0000*	*0.0000*
WAGE	−0.5939***	−0.0517	−0.5420***
	0.0000	*0.8480*	*0.0000*
VAPC	0.0721	2.3146***	−0.5483***
	0.7160	*0.0000*	*0.0040*
PRVSIZE	−0.0803	0.2606*	0.0318
	0.3060	*0.0710*	*0.6720*
POPD	0.1993***	0.3972***	0.2104***
	0.0000	*0.0000*	*0.0000*
EXIT	0.0771***	0.0210	0.0780***
	0.0000	*0.1670*	*0.0000*
ENTRYOTH		0.0783***	
		0.0020	
ENTRYSC			0.0325***
			0.0010
Observations	20,654	20,553	20,554
Left-censored	6508	11,846	7933
Model test	196.22	78.03	188.32
	0.0000	*0.0000*	*0.0000*
Log pseudolikelihood	−37585.8	−30376.0	−33093.6
F-test [ZGINI, INTEG]	2.80	2.29	0.910
	0.0607	*0.1008*	*0.4034*
t-test [ZGINI + INTEG)]	2.21	1.70	1.335
	0.0136	*0.0441*	0.091

For the description of the variables, see Table 1. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The p-values of the tests are in italics. The standard errors (not reported) are robust to heteroskedasticity and autocorrelation. All the explanatory variables are lagged once to avoid simultaneity bias. The variables BRDENS, FDENS, FSIZE, EMPC, WAGE, VAPC, PRVSIZE and POPD are in log terms. Sectoral, regional and year dummies (excluding 2020) are always included but not reported. INTEG is the interaction term between ZGINI and the dummy COVID (2020 = 1). The statistical significance of [ZGINI + INTEG] is assessed by computing the relative standard errors. The model test is the F-test of the joint significance of all explanatory variables.

6. Concluding remarks

This paper has empirically investigated the role of bank structural features on new firms' formation. In assessing this issue, we depart from the extant literature – which provides contrasting theoretical and empirical predictions – and embrace the conceptual perspective offered by the so-called "biodiversity argument" in banking, introduced by Ayadi et al. (2009 and 2010). As a central thesis of this viewpoint, what matters for the financing of the real economy (and systemic financial stability) is the coexistence of different institutional and organizational bank structures in a market, more so than the merits and drawbacks of each one. Indeed, a landscape populated by a variety of bank types – each with its own specificities in terms of business strategies and practices, lending policies and technologies – guarantees that the economy will not count on a single bank model, which could be ill-suited to some (uncertain and unpredictable) market conditions.

As the above standpoint resonates with bio-ecological concepts, the key variables of our analysis take the form of biodiversity indexes computed at the Italian local credit market level and put in relation to the entry rates of manufacturing firms in the period

2009–2020.

The empirical evidence we provide suggests that banking diversity may be paramount for financing the entrepreneurial process, especially when it involves innovative enterprises; thus, we believe it aligns with the biodiversity standpoint in banking. Accordingly, the main policy recommendation of our work is that authorities should design regulations that, by avoiding prioritizing one bank model over another, promote institutional diversity in the banking landscape.

Such a policy recommendation appears even more valuable in light of the insight that local banking diversity might have mitigated the adverse effects on firms' entry rates due to turmoil and uncertainty during the COVID-19 pandemic. An issue, this latter, that for its relevance – and the need to overcome our present analysis's limitations – deserves more in-depth future investigation.

Declaration of competing interest

The authors of the manuscript entitled "Diversity in Banking and New Firm Formation. Insights from the Italian Local Credit Markets" declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2024.01.005.

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