Knowledge and cultural diversity in entrepreneurship: Untangling the relationship

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REGULAR ARTICLE

Knowledge and cultural diversity in entrepreneurship: untangling the relationship

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Abstract
This study investigates the role of cultural diversity and local knowledge stocks for entrepreneurship, focusing on the interplay between the two. We consider the Italian case, where immigration is comparatively low-skilled and originating largely from less advanced economies. Focusing separately on high-tech and low-tech entrepreneurship, we document the coexistence of heterogeneous effects of diversity for entrepreneurship. We find that cultural diversity promotes high-tech entrepreneurship only by high levels of knowledge stocks. In contrast, cultural diversity has a direct, positive effect on low-tech entrepreneurship that is negatively moderated by knowledge. We interpret these findings as the result of two different effects of diversity: diversity promotes high-tech entrepreneurship providing heterogeneous perspectives and evaluations of business opportunities; at the same time, it increases taste heterogeneity, offering low-tech business opportunities to necessity entrepreneurs which become less and less appealing as the knowledge stock of the region increases.

Keywords Cultural diversity · Knowledge stock · Knowledge spillover theory of entrepreneurship · High-tech entrepreneurship · Necessity entrepreneurship

1 Introduction

Most countries globally are experiencing shifts in their demographic composition towards greater cultural diversity (World Bank, 2023). The impacts of cultural diversity on production, labor markets, and consumption are so extensively studied that "the economics of diversity" is emerging as a distinct field (Nathan, 2015). In

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particular, there is established evidence that cultural diversity fosters entrepreneurship (Audretsch et al., 2010; Kemeny, 2017; Nathan, 2015).

Yet, new firm formation is not a positive phenomenon per se. New firms are extremely heterogeneous and often doomed to early failure so they may not be necessarily considered as a potential driver of growth and job creation. The entry of new firms is a very complex phenomenon, characterized by a high degree of heterogeneity where a minority of genuine Schumpeterian innovators are neck to neck to innovative followers, passive replicators and defensive and necessity entrepreneurs (Santarelli & Vivarelli, 2002, 2007). Experience has shown that fostering the creation of start-ups without tight scrutiny of their quality can result in a "bad public policy" (Colombelli et al., 2016; Shane, 2009). In this line of reasoning, the foundation of new businesses may be more or less conducive to technological upgrading and productivity growth according to the different sectors in which it occurs. Obviously enough, new technology-based firms (see Acs & Audretsch, 1990; Audretsch, 1995; Colombo et al., 2004; Colombo & Grilli, 2010) in high-tech manufacturing industries and knowledge-intensive business services play a different role than start-ups in low-tech manufacturing and traditional services (Antonelli et al., 2023).

To analyze this phenomenon, our focus rests on the role of cultural diversity from migrants in new firm formation. Indeed, the migration-entrepreneurship nexus is complex and multifaceted (Nathan, 2015). The sector-specific competencies of immigrants with different nationalities and the culture-specific demand for diverse products and services enlarge the set of entrepreneurial opportunities. Moreover, to the extent that cultural diversity implies heterogeneous cognitive approaches (Alesina & La Ferrara, 2005; Ali et al., 2022; Brixy et al., 2020; Hong & Page, 2001; Kemeny & Cooke, 2017a, 2017b), it entails heterogeneity in the evaluation and perceived profitability of the business opportunities, thus further reinforcing these dynamics (Gallego-Alvarez et al. 2021; Khan et al., 2021; Mirza et al., 2020). As shown in recent studies, the entrepreneurial and inventive activities arising from cultural diversity and skilled immigration may act as "agents of structural change", i.e., factors that drive the diversification of economies into new high-tech domains that allow them to prosper in a changing competitive landscape (Bahar et al., 2022, 2024; Colombelli et al., 2020; Neffke et al., 2018). At the same time, however, immigrant entrepreneurship is frequently concentrated in low-tech industries (Colombelli et al., 2020), as many lower-skilled migrants tend to become 'defensive and necessity entrepreneurs' pulled by unsophisticated demand. Rather than pursuing business ventures driven by market opportunities or innovation, they often start businesses primarily as a way to avoid unemployment (Baumol, 1990). These dynamics highlight the importance of understanding cultural diversity's impact on entrepreneurship as a key factor in driving long-term regional competitiveness.

In this paper, we argue that interplay between knowledge and diversity can provide insights on the mechanism underlying this relationship. To this aim we bridge the economics of diversity literature with the knowledge spillover theory of entrepreneurship (KSTE). The KSTE argues that the knowledge generated by incumbents is not necessarily commercialised by these firms, generating entrepreneurial opportunities for new firms (Acs et al., 2009; Audretsch, 1995; Audretsch & Lehmann, 2005). The absorptive capacity theory (Qian & Acs, 2013) adds that the extent to which the market value of new knowledge is discovered and exploited depends on the capability of entrepreneurs to recognize such opportunities, while the Knowledge Spillover Theory of Entrepreneurship & Innovation (KSTE&I) stresses the relevance of these dynamics for the promotion of innovative entrepreneurship (Audretsch et al., 2025). Cultural diversity can, therefore, foster entrepreneurship in high-knowledge contexts since diverse economic agents perceive and value potential market opportunities differently, which makes the discovery more likely to occur. Population diversity may also lead to the demand for diverse products and services, thus bringing diversified market opportunities that can be exploited by entrepreneurs. This mechanism is more likely to operate at the regional level for less knowledge intensive businesses than for high technology start-ups that are less likely to have a geographically bounded market (Qian, 2013). Moreover, the level of knowledge available in a region can affect the direction of entrepreneurial activity toward either high-tech or low-tech industries.

By grafting these streams of the literature, in this study we endeavour to provide an overview of the factors and mechanisms that are driving the effects of diversity on entrepreneurship and to move one step forward in the analysis of the interaction between cultural diversity and the knowledge endowment of the local system. Specifically, we study whether the effects of the cultural diversity are affected by the local knowledge stock and whether the interaction between cultural diversity and knowledge differs between high- and low-tech entrepreneurship. Indeed, the extant literature has explored many facets of cultural diversity for entrepreneurship (Audretsch & Belitski, 2013; Audretsch et al., 2010, 2018; Kemeny, 2017; Nathan, 2015; Qian, 2013). However, we argue that looking at this relationship from the perspective of the KSTE&I bears an implication that has received comparatively less attention. Indeed, if diversity mainly increases entrepreneurship by broadening the variety of perspectives and cognitive approaches available locally, its effects should increase with the knowledge stocks. Instead, if the relationship is driven by differentiated demand coming from a culturally different population, it could operate independently from the local knowledge stock. Such dynamics are likely different in high- and low-tech sectors. We thus offer a novel contribution to the literature by shedding light on the mechanisms through which cultural diversity impact on different types of entrepreneurship depending on the local knowledge stock.

We address these issues by employing a unique dataset stemming from the combination of different sources of information. We find that cultural diversity promotes high-tech entrepreneurship only by high levels of knowledge stocks. In contrast, cultural diversity has a direct, positive effect on low-tech entrepreneurship that is negatively moderated by knowledge.

This study is organized as follows. In Sect. 1, we revise the relevant literature and develop testable hypotheses. In Sect. 2, we present our empirical application. In Sect. 3, we present and discuss the results and in Sect. 4 a set of robustness checks. Section 5 concludes.

2 Cultural diversity, knowledge diversity and entrepreneurship

The plurality of cultures in firms, cities, and regions may affect entrepreneurship in different ways: talent attraction, diverse ways of perceiving market opportunities, and diversified market demand (for extensive surveys see Nathan, 2014, 2015; Kemeny, 2017). Empirical studies mostly support a positive relationship between cultural diversity and entrepreneurship, but results are not univocal. Studying German regions over 1998–2005, Audretsch et al. (2010), find that cultural diversity positively affects entrepreneurship and is highly significant in the case of technology-oriented start-ups, technology oriented services, and high tech start-ups. Nathan and Lee (2013) find that the migrant status has a positive link to entrepreneurship for firms located in London. Rodríguez-Pose and Hardy (2015) find that diversity amongst highly skilled workers exerts the strongest impact upon start-up intensities in UK regions. In contrast, Cheng and Li (2012) highlight significant differences across sectors in the impact of diversity, and Lee et al (2004) do not find a positive association of new firm creation with the share of the foreign-born population in US metropolitan areas. Similarly, Bishop (2012) finds no impact of local economy-wide ethnic diversity of new firm formation across local unitary authorities and districts in Great Britain over 2001–2007. Distinguishing between tolerance and diversity, Qian (2013) finds that cultural diversity affects entrepreneurship in US cities more strongly than tolerance (measured using the composite gay and bohemian index), concluding that the effects of diversity mainly go through the variety of perceptions of entrepreneurial opportunities and the diversity in consumer demand.

On a parallel ground, the knowledge spillover and absorptive capacity theory of entrepreneurship (Acs et al., 2009; Qian & Acs, 2013) focuses on the diversity of perceived entrepreneurial opportunities as the main mechanism driving the relationship between cultural diversity and entrepreneurship. The knowledge spillover theory of entrepreneurship (KSTE) specifically suggests that the knowledge created by established firms is not always commercialized by them, creating entrepreneurial opportunities for new ventures. The absorptive capacity theory adds that the extent to which the market value of new knowledge is discovered and exploited depends on entrepreneurial absorptive capacity—defined as the ability of an entrepreneur to understand new knowledge, recognize its value, and subsequently commercialize it by creating a firm (Qian & Acs, 2013). According to this view, cultural diversity can foster entrepreneurship since diverse economic agents perceive and value potential market opportunities differently, which makes the discovery and the attitude to exploit such discovery more likely: the more different kinds of people evaluate any given idea, the higher will be the probability that one of these persons will arrive at the conclusion that she wants to commercially exploit it (Audretsch et al., 2010; Qian, 2013). Recently, the KSTE has been extended by the Knowledge Spillover Theory of Entrepreneurship & Innovation (KSTE&I) to stress the relevance of innovative entrepreneurial activities as a potential driver of economic growth and development (Audretsch et al., 2025). In this respect, new firms in high-tech industries and knowledge-intensive services play a different role than those operating in low-tech manufacturing and traditional services.

Drawing on these theories, we argue that the simple presence of cultural diversity at the local level may not translate into innovative entrepreneurship in the lack of sufficiently high levels of the knowledge stock. A higher knowledge stock facilitates overcoming differences in culture, makes knowledge exchange easier and enhances knowledge spillovers (Audretsch, 2023). In other words, the variety in cultural perspectives may not translate into business-relevant knowledge due to lack of absorptive capacity in the local system. Yet, contexts rich in knowledge may increase the absorptive capacity in the local system (Audretsch et al., 2010; Qian, 2013) and, in turn, positively affect the identification of new entrepreneurial opportunities and the creation of new firms. All these mechanisms are likely to operate especially when considering high-tech entrepreneurship.

In this line of reasoning, we postulate the following hypothesis:

Hp1: The regional knowledge stock positively moderates the impact of cultural diversity on high-tech entrepreneurship.

In many contexts, like in the Italian case, where immigration is comparatively low-skilled and originating largely from less advanced economies, knowledge available in the external environment may play a more limited role in driving the relationship between cultural diversity and entrepreneurship especially in less knowledge intensive sectors. For example, in some service sectors, such as retail trade, cultural diversity can lead to more entrepreneurship mostly through diversified market demand. In fact, culturally specific needs and habits can create new business opportunities as in the case of diverse food suppliers, restaurants and other retail shops satisfying specific needs of a diverse population. At the local level, this mechanism may play a role in creating less knowledge intensive entrepreneurship serving the local market and does not require the presence of a high levels of the knowledge stock. As argued by Santarelli and Vivarelli (2007), entry is not always the consequence of favourable market conditions or new technological opportunities, but it may also respond to the need to exit from unemployment or from disadvantaged working conditions. This type of necessity-driven entrepreneurship is more likely to prevail in less knowledge-intensive regions.

In this line of reasoning, we formulate our second hypothesis:

Hp2: The impact of cultural diversity on low-tech entrepreneurship does not depend on the local knowledge stock.

Overall, we may assume that the relationship between cultural diversity and entrepreneurship is moderated by the local knowledge stock but with different expectations in high- and low-tech sectors. In high-tech sectors, we may expect a prevalence of opportunity-driven entrepreneurship where cultural differences among people result in different ways of evaluating new ideas, thus facilitating knowledge creation and knowledge spillovers. To generate entrepreneurship in these sectors, regions require sufficiently high levels of absorptive capacity (Cohen & Levinthal, 1990) and therefore sufficiently high levels of the knowledge stock. In less knowledge-intensive sectors, the relationship between cultural diversity and entrepreneurship may be mostly driven by necessity-driven entrepreneurship and differentiated demand needs coming from a diverse population (e.g. retail services), with little role for the local absorptive capacity. In this line of reasoning, the knowledge stock may not play a moderating role in the relationship between cultural diversity and low-tech entrepreneurship. A similar reasoning can be applied to the difference between high- and low-skilled immigrants (Cooke & Kemeny, 2017; Suedekum, et al., 2014; Trax et al., 2015). In a robustness check, we will thus test the robustness of our results to distinguishing our measures of diversity by high- and low-skilled immigrants.

3 Variables, data, and methodology

In line with recent contributions, we empirically test our arguments at a relatively fine-grained scale, i.e., Italian NUTS 3 regions, over the 2002–2015 period. Indeed, a condition for the emergence of knowledge spillovers and entrepreneurship is geographic proximity (Audretsch & Feldman, 1996) and, specifically for our research question, the proximity between natives and foreigners, which enables intercultural interaction (D'Ambrosio et al., 2019). Hence, the regional unit of analysis must be narrowly defined to measure a localized phenomenon, yet large enough to capture knowledge spillovers (Audretsch & Lehmann, 2005; Colombelli & Quatraro, 2018). Italian NUTS3 regions appear well suited to comply with these requirements, with their small size compared to other administrative units in the EU. Their considerable heterogeneity in start-up rates, production structure, and cultural diversity conveniently provides variation to measure the phenomenon of interest.

3.1 Variables

3.1.1 Dependent variables

In line with previous studies by Audretsch and Lehmann (2005) and Bonaccorsi et al. (2013), we measure new firm formation as the count of newly registered firms in province *i* and year *t*. To test our hypotheses, we will study the relationship between knowledge diversity in high-tech and low-tech entrepreneurship separately. We consider as "high-tech" all newly founded firms in manufacturing industries and knowledge intensive services according to the Eurostat 3-digit NACE rev 1.1 taxonomy of high-tech industries and knowledge intensive services.[1] These are labelled $HIGH\_TECH_{i,t}$ in our data. Similarly, we consider as "low-tech" all new businesses in low-tech manufacturing industries and less knowledge intensive services. We refer to them as $LOW\_TECH_{i,t}$. To identify high- and low-tech firms in the data, we leverage detailed 3-digit level information on newly founded firms' industries.

[1] The classification is available at https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm. Given that sectoral information post 2009 are classified based on the NACE rev2 classification, we first convert all sectoral data to NACE rev1.1 and then distinguish them by their level of technological intensity.

3.1.2 Independent variables of interest

Cultural diversity ($ENTROPY_{i,t}$). Our hypotheses concern the link between cultural diversity and entrepreneurship. According to Alesina et al., (2016, 105), the most accurate operationalization of cultural diversity is provided by birthplace diversity. This captures the extent to which people have been exposed to different environments, education, cultures, and have developed different cognitive approaches to problem-solving, and is able to distinguish between first- and second-generation migrants. Due to data availability, we measure the cultural diversity of the resident population ($ENTROPY_{i,t}$) based on the nationalities of the foreign residents in the region, rather than on birthplaces. Yet, the vast majority of foreign citizens residing in Italy are also foreign-born, making the two measures effectively equivalent (the share is as high as 99% in our considered timeframe for the working-age population; Colombelli et al., 2020).

As pointed out by Biamann and Kearney (2010) and Kemeny (2017), diversity can be conceptualized and measured in different ways. When diversity is perceived as variety, as in the case of cultural diversity, most studies employ the fractionalization or the entropy index.

The fractionalization index is 1 − H, where H is a standard Herfindahl-Hirschmann index of the concentration of nationalities in a given location. It essentially measures the probability that, taking two random individuals in a location, they share the same origin. The Shannon entropy index similarly draws on the relative frequency of nationalities in a region but multiplies the shares by the log of the inverse of the shares to capture both variety and balance of the groups (Harrison & Sin, 2006; Junge, 1994; Stirling, 2007). Hence, the fractionalization index is recommended when the different groups are of comparable sizes, and the Shannon index is preferred when group sizes are unbalanced (Kemeny, 2017). Given that the shares of a minority of origin countries account for most immigrant population in many regional economies, we opt for the Shannon index in our application. Denoting with s_c the relative frequency of country c citizenship in region i (including the Italian citizenship), we measure regional cultural diversity ($ENTROPY_{i,t}$) as

$$ENTROPY_{i,t} = -\sum s_c ln(s_c). \tag{1}$$

Knowledge stock ($KSTOCK_{i,t}$). Knowledge stock may be operationalized from the input or the output side (Ács et al., 2009). Due to limitations on the NUTS3-level availability of data on knowledge inputs like human capital and R&D expenditure, we focus on knowledge output side and measure knowledge stocks based on patent application data. We are aware of the limitations of patents as a measure of knowledge and innovation—not all patents represent innovation, many innovations are not patented, the propensity to patent differs across industries and patents underestimate innovation in service industries. Yet, patent applications remain a widespread used proxy due to their availability at different levels of aggregation and over time. For each NUTS3 region, we compute patent stocks by the permanent inventory method. The initial value of the stock is calculated as

$$KSTOCK_{i,t=0} = (1 + \rho) / (\rho + \delta) \times \dot{h}_{i.t=0}, \tag{2}$$

where ρ is the average geometric growth rate for the patent applications series (8%), δ is the rate of obsolescence, set at 15% per annum (Colombelli & Quatraro, 2018; Hall et al., 2005), and $\dot{h}_{\mathrm{i,t}}$ is the flow of patent applications in the base year. Given that our panel start in 2002, we take 2000 as the base year for calculating the stocks.

The values of the subsequent years are obtained as follows:

$$KSTOCK_{i,t} = \dot{h}_{i,t} + (1 - \delta)KSTOCK_{it-1}, \tag{3}$$

where $\dot{h}_{\mathrm{i,t}}$ is the flow of patent applications in region i and year t.

Finally, to normalize the variable with respect to province size and to mitigate collinearity with other variables, we divide it by the number of firms (measured in thousands), so that our capital stock variable will capture knowledge capital stocks per 1000 firms.

3.1.3 Control variables

Consistent with previous literature, we also include a set of control variables in the empirical analysis. All of them are included with a three-year lag.

Incumbents ($INCUMB_{i,t}$). To control for region size, we include the total number of incumbent firms. In a negative binomial regression, this is akin to studying the effects of our regressors on entry rates, as for instance in Audretsch et al. (2010). We do not restrict the coefficient of $INCUMBENT_{i,t}$ to be equal to one, although it empirically turns out to be very close to this value.

Entry-exit ratio ($ENTRY\_EXIT_{i,t}$). A dynamic demography of firms in the past triggers opportunities for prospective entrepreneurs in the future, as entrepreneurship is a process that involves cycles of adaptation and adjustment among mutually dependent actors (Staber, 2005), and it stimulates the local development of local institutions and support services for startups such as incubators and venture capital (Aernoudt, 2004; Cumming & Dai, 2010; Peters et al., 2004; Seasholes & Zhu, 2010). To control for this important confounding factor, we include the entry-to-exit rate of firms among our regressors, which we expect to positively affect high-tech entrepreneurship. We measure entry-to-exit rates with the lagged ratio of newly founded firms to closed firms in each province.

Per capita GDP ($PC\_GDP_{i,t}$). We include per-capita GDP in our analysis, measured as the ratio between GDP (constant values at 2000 prices) and population, to control for the strong role of demand as an incentive for prospective entrepreneurs (Carree & Thurik, 2006).

Financing risk ($FIN\_RISK_{i,t}$). Entrepreneurial initiatives critically rely on access to financial resources (Blumberg & Latterie, 2008). Prospective entrepreneurs that lack personal assets may be prevented from accessing credit in high risk environments if banks are unable to accurately assess the risk of their entrepreneurial projects (Evans & Jovanovic, 1989; Johansson, 2000; Stiglitz & Weiss, 1981). On the other hand, riskier environments may yield greater returns. In line with this literature, we include the loan decay rate to control for the overall level of risk of the local financial system.

Labor productivity ($LABOR\_PROD_{i,t}$). Immigration rates and cultural diversity may correlate with labor productivity, as immigrants may be attracted to provinces with greater productivity that offer broader employment opportunities. To control for this correlation, we include a measure of labor productivity in our analysis, measured as the ratio of province value added over total employment.

Manufacturing share ($MANUF\_SH_{i,t}$). Immigration rates and cultural diversity may also correlate with the composition of the local economy, as immigrants tend to locate in provinces with greater shares of manufacturing employment. To control for this correlation, we include the share of manufacturing employment over total employment.

Imports and export rates ($IMPORT\_RATE_{i,t}$ *and* $EXPORT\_RATE_{i,t}$). Immigration, knowledge and cultural diversity may correlate with the openness of the province to international trade, as trade represents a channel for knowledge diffusion. We proxy this openness with the shares of imports and exports over GDP.

3.2 Data

We operationalize our dependent variable with the number of new businesses registered for value added tax (VAT) in high and low-tech sectors. The source for these data is the Movimprese dataset maintained by the Union of the Chambers of Commerce (Unioncamere), that includes details on their three-digit NACE code sectoral classification. These statistics exclude smaller businesses that are not subject to compulsory registration with the Chamber of Commerce.

Our data about the cultural diversity of residents and the immigration rate are drawn from publicly available ISTAT data on yearly stocks of the resident population with foreign citizenship. They are disaggregated by NUTS 3 region of residence and country of citizenship and are available since 2002.

The knowledge stock measure draws on the information contained in patent documents from the OECD RegPat Database. These data include applications to the European Patent Office (EPO) and applications to national patent offices, which go back to 1920 in the case of some patent authorities. We assign patent applications to NUTS 3 regions based on the inventors' addresses. Applications with several inventors residing in different regions are assigned to the relevant regions based on their respective shares. Our study is limited to applications submitted by inventors residing in Italian regions.

The data about incumbent firms and entry-exit ratios are drawn from the Movimprese database. The data about GDP, population, labor productivity and manufacturing rates originate from the Cambridge Econometrics regional database. Finally, the data on imports and exports rate, as well as on financing risk, are retrieved from the ISTAT website.

Over these years, the data are available for 103 Italian NUTS3 regions, leading to a maximum of 1133 observations to our empirical analysis. We exclude the province

Table 1 Summary statistics

Variable	Mean	Std. Dev.	Min	Max
$HIGH\text{-}TECH_{i,t}$	500.15	719.64	47.00	5665.00
$LOW\text{-}TECH_{i,t}$	1198.91	1382.11	155.00	9581.00
$INCUMB_{i,t}$	10.67	0.71	9.08	13.08
$PC\_GDP_{i,t}$	10.00	0.26	9.44	10.76
$ENTRY\_EXIT_{i,t}$	− 0.02	0.17	− 0.85	0.58
$LABOR\_PROD_{i,t}$	4.00	0.12	3.67	4.33
$IMPORT\_RATE_{i,t}$	− 1.95	0.96	− 4.92	0.72
$EXPORT\_RATE_{i,t}$	− 1.84	1.13	− 5.62	0.28
$FIN\_RISK_{i,t}$	0.85	0.71	− 1.75	3.00
$MANUF\_SH_{i,t}$	− 1.76	0.44	− 2.87	− 0.92
$KSTOCK_{i,t}$	1.29	1.10	− 1.99	3.49
$ENTROPY_{i,t}$	1.07	0.11	0.63	1.28
$ENTROPY\_H\_EDU_{i,t}$	1.54	0.08	1.27	1.70
$ENTROPY\_L\_EDU_{i,t}$	1.37	0.12	0.94	1.59

Observations: 1022. All regressors are lagged 3 years and log-transformed

of Prato, which is a clear outlier, from our analysis.[2]Missing data issues affecting mainly the new provinces established in 2005 limit our final estimation sample to 1022 observations and 94 provinces over the 2002–2015 period. Lagging our regressors 3 years (see below), the effective number of years available for estimation is 10.

Table 1 reports the summary statistics of our variables.

To mitigate unobserved heterogeneity without absorbing too much variation in our phenomenon of interest, our identification strategy exploits the time variation along with the NUTS3-level cross-sectional variation within NUTS 2 regions. Table 2 displays the correlation matrix. As we could expect, size is highly correlated with new firm formation. Knowledge stock correlates with per-capita GDP, labor productivity, import and export rates, and manufacturing shares. Cultural variety correlates with the knowledge stock, as well as with per-capita GDP, labor productivity and manufacturing shares, confirming the importance to control for this confounding factors. Nonetheless, collinearity does not appear to significantly affect our estimates, as we tested in a series of variance inflation factor (VIF) tests applied to the linear regressions corresponding to our specifications. Indeed, the mean VIF for our specifications never exceeds 4. Closer inspection of the regression diagnostics reveals that the highest individual VIF values are driven by the correlation between the province-level GDP and the fixed effects, while no relevant collinearity issues remain for the other variables. The individual VIF associated with our cultural variety variables is also below 3.

[2] Immigration rates are much higher in this province than in other provinces in Italy, but diversity is much smaller due to a very large Chinese community located in the area.

Table 2 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$HIGH\text{-}TECH_{i,t}$	1.00													
2	$LOW\text{-}TECH_{i,t}$	0.90	1.00												
3	$INCUMB_{i,t}$	0.77	0.83	1.00											
4	$PC\_GDP_{i,t}$	0.43	0.25	0.28	1.00										
5	$ENTRY\_EXIT_{i,t}$	0.17	0.24	0.22	0.06	1.00									
6	$LABOR\_PROD_{i,t}$	0.41	0.23	0.25	0.84	−0.10	1.00								
7	$IMPORT\_RATE_{i,t}$	0.19	0.08	0.12	0.53	−0.02	0.60	1.00							
8	$EXPORT\_RATE_{i,t}$	0.09	−0.01	0.06	0.63	−0.09	0.63	0.84	1.00						
9	$FIN\_RISK_{i,t}$	−0.12	−0.08	−0.08	−0.49	−0.16	−0.22	−0.21	−0.20	1.00					
10	$MANUF\_SH_{i,t}$	−0.01	−0.10	0.01	0.58	−0.06	0.46	0.57	0.78	−0.26	1.00				
11	$KSTOCK_{i,t}$	0.24	0.11	0.18	0.82	−0.07	0.79	0.60	0.74	−0.30	0.71	1.00			
12	$ENTROPY_{i,t}$	0.26	0.22	0.24	0.62	0.16	0.52	0.34	0.41	−0.32	0.37	0.61	1.00		
13	$ENTROPY\_H\_EDU_{i,t}$	0.15	0.03	0.12	0.56	0.13	0.45	0.26	0.31	−0.37	0.27	0.49	0.69	1.00	
14	$ENTROPY\_L\_EDU_{i,t}$	0.24	0.22	0.24	0.57	0.16	0.46	0.31	0.37	−0.32	0.35	0.57	0.99	0.63	1.00

Observations: 1022

3.3 Methodology

The discrete and non-negative nature of our dependent variable motivates the adoption of count data models (Cameron & Trivedi, 2015; Hausman et al., 1984) to estimate our relationship of interest. As suggested by the summary statistics reported in Table 2, our dependent variable is overdispersed, hence the negative binomial estimator can be expected to be more efficient than the Poisson estimator (Greene, 2003). Our baseline model will be the following:

$$Y_{i,t} = \exp(\beta_0 + \beta_1 ENTROPY_{i,t-3} + \beta_2 KSTOCK_{i,t-3} + \beta_3 ENTROPY_{i,t-3} \times KSTOCK_{i,t-3} + Z\gamma + \rho_r\delta + \psi_t\vartheta + \epsilon_{i,t}) \tag{4}$$

With $Y = \{HIGH\_TECH;\ LOW\_TECH\}$. Besides the variables that we have already identified, Z represents a vector of control variables, ρ_r is a vector of NUTS2 level regional dummies, ψ_t a vector of time dummies, $\beta_0, \beta_1, \beta_2, \beta_3, \gamma, \delta, \vartheta$ are parameters or parameter vectors to be estimated, and $\epsilon_{i,t}$ is a disturbance component with a gamma distribution of mean 1 and variance α, where α is an overdispersion parameter. As anticipated in Sect. 3, we follow Colombelli and Quatraro (2018) in lagging the regressors three years to account for the time needed for the local system to adjust to changes in the demographic and knowledge structure.

To simplify interpretation, we log-transform all regressors to allow the coefficients to be interpreted as elasticities. We are mainly interested in the marginal effect of the interaction *ENTROPY* × *KSTOCK* on *HIGH_TECH* and *LOW_TECH,* which will address Hypotheses 1 and 2, respectively. In this regard, we take stock of the fact that the coefficient of the interaction effects is not necessarily equal to the marginal effect of the interaction in non-linear models (Ai & Norton, 2003), even though the issue is less severe in exponential models like the negative binomial. Still, we can study how the marginal effect of cultural diversity changes with the knowledge stock.

We also study the extent to which our results can be given a causal interpretation in two different ways. First, with a view to maintain consideration of the count nature of the dependent variable, we implement a control function approach. Second, we confirm the robustness of our results by implementing the corresponding linear instrumental variables approach. In this case, we log-transform the dependent variable.[3]

In both cases, we draw on a standard shift-share instrument (Altonji & Card, 1991), that has been applied to the analysis of diversity since Ottaviano and Peri (2006). The critical step in building the instrument for cultural diversity is to impute the stocks of immigrants by province and country of origin. We compute imputed immigration stocks by multiplying the share of immigrants from each country over total immigration at the start of the period with the annual country-specific growth rates nation-wide. Start-of-period immigration shares proxy for the size of the ethnic enclave at the beginning of the period, which is a strong attractor of future co-ethnic immigration irrespective of the economic and business opportunities offered by

[3] We add one unit to the dependent variable to tackle the indeterminacy of the log of zero in case no firms have been founded in a province in a particular year.

the province (Card, 2001). This is important to identify the province-level variation in the instrument. The time dimension of the instrument (i.e., the shifter) is identified with the nation-wide growth in immigration stocks by year and country. This accounts for country-specific push factors (e.g., conflicts, economic conjuncture, EU accession) that may exogenously change the immigration stocks from particular countries. Combining the shares and the shifters we obtain an imputed immigration stock for every country. Finally, the resulting imputed stocks are aggregated based on the entropy formula to get the instruments for *ENTROPY*.

In the control function approach, we employ the instrument in a first-stage regression of *ENTROPY* on the instrument and control variables, save the residuals and plug them into our main second-stage negative binomial regression. The coefficients of the residuals provide a measure of the effects of endogeneity in immigration and immigrant entrepreneurship on our outcomes of interest (Wooldridge, 2015). In the IV-GMM approach, we employ the instrument to isolate the predicted component of cultural diversity that is plausibly exogenous.

4 Econometric results

In Table 3, we show the baseline regressions reporting the effects of cultural diversity on high-tech and low-tech entrepreneurship. Columns 1–3 report the results for high-tech entrepreneurship, while Columns 4–6 those for low-tech entrepreneurship.

We consider high-tech entrepreneurship first. In column 1, we include a control-only model. In line with previous findings in the literature, the results indicate that high-tech firm formation increases with the size of the economy, as shown by the positive and significant coefficient of *INCUMB* and of the lagged entry-exit rate *ENTRY_EXIT*. As expected, more dynamic economies trigger cumulative dynamics that provide more opportunities for firm creation, facilitating the circulation of unexploited knowledge and ideas that materialize in new businesses. Results also suggest that the effect of labor productivity *LABOR_PROD* prevails over that of per-capita GDP *PC_GDP* in triggering high-tech entrepreneurship, conditional on other closely correlated variables and on the time and NUTS2 fixed effects. The positive and significant coefficient estimated for *IMPORT_RATE* further suggests that imports are a significant channel of access to external knowledge for NUTS3 regions. Instead, *EXPORT_RATE, FIN_RISH* and *MANUF_SH* do not significantly affect high-tech entrepreneurship, conditional on the other covariates.

In column 2, we augment the model with our knowledge proxy, *KSTOCK*. This variable turns out positive and significant, confirming the positive role of knowledge stock on high-tech entrepreneurship. In line with the knowledge spillover and the recombinant theory of entrepreneurship, a broader knowledge stock implies that more ideas are exchanged and can be combined to generate new knowledge, ideas, and business opportunities in complex and high-tech realms.

Table 3 Baseline regression results

	High-tech			Low-tech		
	(1)	(2)	(3)	(1)	(2)	(3)
$INCUMB_{i,t\text{-}3}$	1.068***	1.058***	1.057***	1.031***	1.024***	1.022***
	(0.0125)	(0.0126)	(0.0126)	(0.0105)	(0.0106)	(0.0105)
$PC\_GDP_{i,t\text{-}3}$	− 0.0486	− 0.0770	− 0.0721	− 0.527***	− 0.549***	− 0.544***
	(0.0839)	(0.0834)	(0.0836)	(0.0782)	(0.0787)	(0.0790)
$ENTRY\_EXIT_{i,t\text{-}3}$	0.116***	0.0815*	0.0753*	0.164***	0.139***	0.133***
	(0.0435)	(0.0425)	(0.0425)	(0.0353)	(0.0349)	(0.0346)
$LABOR\_PROD_{i,t\text{-}3}$	0.799***	0.595***	0.560***	0.857***	0.717***	0.684***
	(0.146)	(0.146)	(0.144)	(0.127)	(0.123)	(0.123)
$IMPORT\_RATE_{i,t\text{-}3}$	0.0308***	0.0304***	0.0323***	0.0161	0.0150	0.0171
	(0.0113)	(0.0114)	(0.0112)	(0.0113)	(0.0111)	(0.0110)
$EXPORT\_RATE_{i,t\text{-}3}$	− 0.0136	− 0.0164	− 0.0182	− 0.0185	− 0.0202	− 0.0220
	(0.0151)	(0.0153)	(0.0153)	(0.0145)	(0.0142)	(0.0144)
$FIN\_RISK_{i,t\text{-}3}$	0.0115	0.0102	0.0102	− 0.00221	− 0.00309	− 0.00312
	(0.0116)	(0.0112)	(0.0111)	(0.00967)	(0.00957)	(0.00952)
$MANUF\_SH_{i,t\text{-}3}$	0.0424	− 0.00753	0.00233	0.0807***	0.0457*	0.0558*
	(0.0278)	(0.0297)	(0.0311)	(0.0265)	(0.0275)	(0.0287)
$KSTOCK_{i,t\text{-}3}$		0.0849***	0.0793***		0.0631***	0.0576***
		(0.0150)	(0.0156)		(0.0132)	(0.0137)
$ENTROPY_{i,t\text{-}3}$			0.112			0.110**
			(0.0738)			(0.0557)
_cons	− 7.990***	− 7.005***	− 6.998***	− 2.069***	− 1.364**	− 1.359**
	(0.594)	(0.588)	(0.590)	(0.561)	(0.585)	(0.583)
lnalpha	− 3.612***	− 3.655***	− 3.658***	− 3.904***	− 3.935***	− 3.939***
	(0.0619)	(0.0645)	(0.0639)	(0.0539)	(0.0541)	(0.0540)
N	1022	1022	1022	1022	1022	1022

Negative binomial regression coefficients. Robust standard errors in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. All specifications include NUTS2 region fixed effects and time dummies. All regressors are lagged three years and log-transformed

In column 3, we add our measure of cultural diversity, *ENTROPY*. Our estimates show that, on average, the cultural diversity of the province does not, per se, significantly increase high-tech entrepreneurship rates.

Turning to low-tech entrepreneurship, Column 4 confirms that the key drivers of entrepreneurship apply throughout sectors and are not limited to the high-tech realm. In particular, *INCUMB*, *ENTRY_EXIT,* and *LABOR_PROD* maintain their positive and significant coefficient: the spillover effects from entrepreneurial dynamism and productivity trigger entrepreneurship in several realms, not exclusively high-tech. Moreover, we note that low-tech entrepreneurship increases with the manufacturing orientation of the province, again pointing at the spillover effects emerging from a strong manufacturing base. Finally, consistent with

Santarelli and Vivarelli (2007), we find that low-tech entrepreneurship also negatively and significantly correlates with per-capita GDP, pointing at the relevant role of low-tech "defensive" entrepreneurship as a survival strategy in contexts of limited economic performance.

Adding our proxy for knowledge stocks *KSTOCK* in Column 5, we also confirm the role of knowledge spillovers in low-tech realms. Intuitively, not all unexploited opportunities generated by a strong knowledge base are high-tech opportunities. Rather, our results suggest that a strong knowledge base triggers opportunities in low-tech sectors, possibly complementary to higher-tech ones in the value chain. It is worth noticing that our measure of low-tech entrepreneurship encompasses a variety of sectors ranging from low-tech manufacturing such as manufacturing of basic metals and food, which may be complementary to higher-tech activities, to less knowledge-intensive services such as retail trade, accommodation and food service activities.

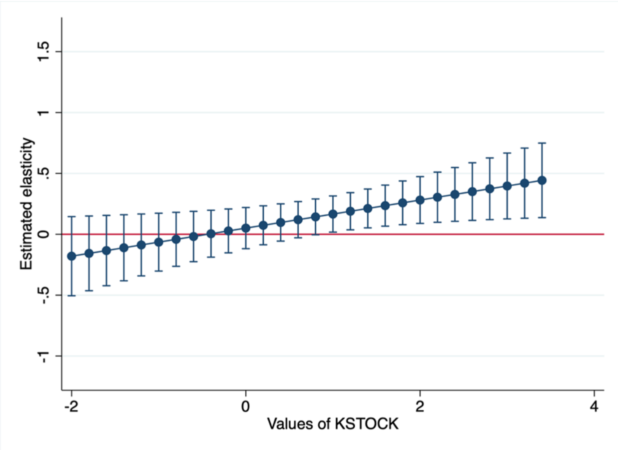
Finally, adding *ENTROPY* to the picture, Column 6 shows a positively and significant role of cultural diversity for low-tech entrepreneurship. As discussed in Sect. 2, this result may be explained in different ways. One explanation is that cultural diversity in the region increases the variety of ways in which business opportunities are perceived among different prospective entrepreneurs. Another explanation is that cultural diversity brings heterogeneous tastes, hence directly broadens the set of products and services that are supplied.

To dig deeper into the understanding of this result, we explore the moderating effects of cultural diversity on the knowledge stock in Fig. 1. The figure reports the elasticities of the knowledge stock at different levels of cultural diversity estimated from an underlying negative binomial regression model where *KSTOCK* is interacted with *ENTROPY*. Panel 1a shows this relationship for high-tech entrepreneurship, while the Panel 1b shows it for low- tech.[4]

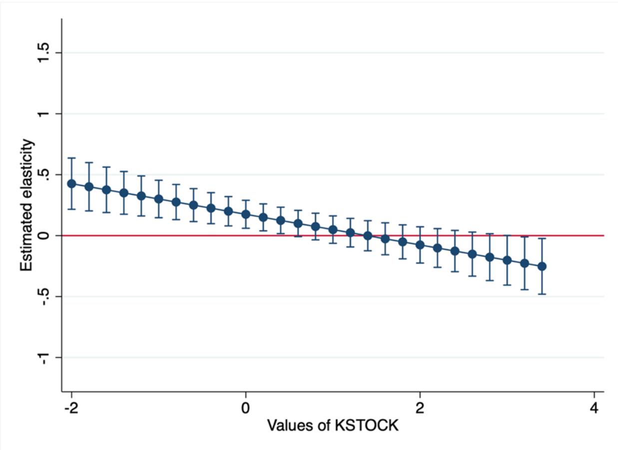
The two panels display remarkably different patterns, suggesting rather different underlying mechanisms. For what concerns high-tech entrepreneurship (Fig. 1a), we find that knowledge stocks magnify the effects of cultural diversity. In contrast, the estimates for low-tech entrepreneurship show the opposite pattern (Fig. 1b).

We interpret this intriguing result as follows. The positive moderating effect identified for high-tech entrepreneurship in Fig. 1a is consistent with the interpretation that cultural diversity has a stronger effect on entrepreneurship in local systems hinging on greater absorptive capacity. Interestingly, the graph clearly shows that the local knowledge stock makes the effect of diversity on high-tech entrepreneurship turn from negative to positive. We interpret this result as a sign that a richer knowledge stock facilitates overcoming differences in culture, making knowledge exchange easier and enhancing knowledge spillovers (Griliches, 1992). At the same time, a broader knowledge stock produces more unexploited opportunities for high-tech entrepreneurship, and a more diverse set of cultures increases the ability of the local system to grasp them and to turn them into commercial ends. In short, the interplay of cultural diversity and knowledge stocks appears to broaden

[4] The estimated elasticity of *ENTROPY* when *KSTOCK* is close to its mean value correspond the ones obtained for the non-interacted models reported in Table 3.



a. High-tech entrepreneurship



b. Low-tech entrepreneurship

Fig. 1 The moderating effect of knowledge stocks on cultural diversity. The figures report the estimated elasticities of high-tech and low tech entrepreneurship on KSTOCK for different values of ENTROPY estimated from negative binomial regressions including interaction effects between the two variables

the absorptive capacity of the local system and to turn knowledge into high-tech entrepreneurship (Lee et al., 2004; Qian & Acs, 2013). This evidence appears very consistent with Hypothesis 1.

Turing to low-tech entrepreneurship, the negative interaction effect between knowledge stocks and cultural diversity reported in Fig. 1b points, instead, to a substitution effect. This result implies that, when the knowledge stock is comparatively low, the effect of diversity on low-tech entrepreneurship is at its maximum. This evidence does not support Hypothesis 2. A possible interpretation is as follows. Low-tech ventures supplying ethnic enclave services (e.g., ethnic food suppliers, telephone and money transfer services) are a common way to escape unemployment for foreign workers, and cultural diversity increases the demand for such services. As knowledge stocks increase, the effects of cultural diversity on low-tech ventures decreases, arguably because there are more channels and opportunities for firm formation in higher-tech realms and the expected returns from low-tech businesses may be lower. In short, we interpret this result as an indication that cultural diversity triggers necessity entrepreneurship particularly when the knowledge stock is low.

5 Robustness checks

A critical source of concern for the interpretation of our effects as causal effects is the self-selection of immigrants into provinces that provide comparatively better opportunities for foreign residents and entrepreneurs, which affects the cultural composition of the region. Unobserved factors making the provinces attractive for foreign residents and entrepreneurs will probably correlate with the province overall entrepreneurship rates and confound the results, with the 3-year lags only having a negligible effect in mitigating the endogeneity. Moreover, considering the diversity of all immigrants together may hinder substantially heterogeneous effects of high- and low-skilled immigrants. For these reasons, we implement a set of robustness checks addressing endogeneity concerns in Sect. 5.1 and skills heterogeneity in Sect. 5.2.

5.1 Endogeneity

The first approach that we implement to address endogeneity is a control function approach. As mentioned, we augment our baseline negative binomial regressions with the residuals of a set of first-stage regressions of our variables of interest on instruments, controls and fixed effects. Under the assumption of instrument exogeneity, these residuals are intended to purge the effect of diversity measures from the endogenous component of immigrants' location choices, and to allow for a causal interpretation of our variables of interest (Wooldridge, 2015).

Specifically, we implement a first-stage regression to predict the value of our cultural diversity measure, and retain the corresponding first-stage residuals in a new variable called $R\_ENTROPY_{i,t}$. Then, we include *R_ENTROPY* in our main specifications with a three-year lag along with the other covariates, interacting both *ENTROPY* and *R_ENTROPY* with *KSTOCK*. As the residuals are estimated, we bootstrap the standard errors. We do so for both high-tech and low-tech entrepreneurship.

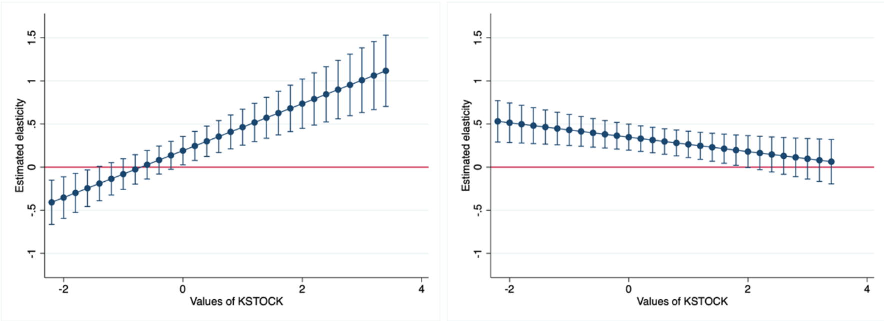
We report the results of this exercise in Table 4. The results in column (1) confirm the insignificant causal effect of diversity on high-tech entrepreneurship and do not raise substantial endogeneity concerns, as the coefficient of the first-stage residual is insignificant. For what concerns low-tech entrepreneurship, column (2) shows significant evidence of endogeneity, with higher-than-predicted values of cultural diversity correlating negatively with low-tech entrepreneurship. Yet, we still

Table 4 Control function results

	(1) High-tech	(2) Low-tech
$INCUMB_{i,t\text{-}3}$	1.057***	1.020***
	(0.0138)	(0.0105)
$PC\_GDP_{i,t\text{-}3}$	−0.0694	−0.527***
	(0.0843)	(0.0981)
$ENTRY\_EXIT_{i,t\text{-}3}$	0.0742	0.128***
	(0.0472)	(0.0358)
$LABOR\_PROD_{i,t\text{-}3}$	0.549***	0.614***
	(0.138)	(0.156)
$IMPORT\_RATE_{i,t\text{-}3}$	0.0329**	0.0216*
	(0.0134)	(0.0117)
$EXPORT\_RATE_{i,t\text{-}3}$	−0.0188	−0.0263*
	(0.0151)	(0.0160)
$FIN\_RISK_{i,t\text{-}3}$	0.0103	−0.00271
	(0.00984)	(0.00878)
$MANUF\_SH_{i,t\text{-}3}$	0.00515	0.0755**
	(0.0365)	(0.0322)
$KSTOCK_{i,t\text{-}3}$	0.0780***	0.0489***
	(0.0174)	(0.0147)
$ENTROPY_{i,t\text{-}3}$	0.138	0.287***
	(0.0982)	(0.0710)
$R\_ENTROPY_{i,t\text{-}3}$	−0.0648	−0.445***
	(0.162)	(0.118)
_cons	−6.999***	−1.494**
	(0.703)	(0.682)
lnalpha	−3.658***	−3.954***
	(0.0592)	(0.0528)
N	1022	1022

Negative binomial regression coefficients. Bootstrapped standard errors in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. All specifications include NUTS2 region fixed effects and time dummies. All regressors are lagged three years and log-transformed

estimate a strongly positive and significant causal effect of cultural diversity on low-tech entrepreneurship. Remarkably, purging the effect of cultural diversity from its endogenous component, the magnitude of the effect becomes almost three times as large as previously estimated. This suggests that, not correcting for endogeneity, there may be omitted factors correlating positively with diversity and negatively with low-tech entrepreneurship that negatively bias our estimates of the effects of diversity. Such a downward bias may be due to the imperfect measurement of cultural diversity based exclusively on official data on foreign residents, which underestimates the cultural diversity stemming from undocumented and second-generation migrants.



a. High-tech entrepreneurship **b. Low-tech entrepreneurship**

Fig. 2 The moderating effects of knowledge stocks on cultural diversity—control function results. The figures report the estimated elasticities of high-tech and low tech entrepreneurship on KSTOCK for different values of ENTROPY estimated from negative binomial regressions including interaction effects between the two variables and a control function

Turning to the interaction effects of *ENTROPY* with *KSTOCK*, we confirm previous findings. Once again, while knowledge magnifies the effects of *ENTROPY* for high-tech entrepreneurship, it dampens its effects for low-tech entrepreneurship (Fig. 2a, b).[5]

In Table 5, we report the corresponding IV-GMM estimates, where, as mentioned earlier, we log-transform the dependent variable to obtain results that are comparable with the above estimates. These linear models yield very similar insights to those estimated via negative binomial regressions. The first-stage F-tests confirm the strength of the enclave instrument as a predictor of diversity. Once again, we estimate positive effects of *ENTROPY* only for low-tech entrepreneurship and, again, the estimated elasticities are larger than those obtained in the baseline model.

Previous findings are also confirmed for what concerns the interaction effects of *ENTROPY* with *KSTOCK*. Once again, the knowledge stock magnifies the effect of *ENTROPY* for high-tech entrepreneurship, and it reduces it for low-tech entrepreneurship (Fig. 3a, b). Reassuringly, the estimates are virtually identical to those obtained with the control function approach.

Overall, while there is evidence of endogeneity in the residential choices of immigrants, there is also evidence of a causal effect of diversity in increasing low-tech entrepreneurship. Moreover, we confirm that *KSTOCK* magnifies the effect of cultural diversity in high-tech entrepreneurship, and substitutes for it in low-tech entrepreneurship.

[5] The estimated interaction effect of *R_ENTROPY* with *KSTOCK* is negative and significant for high-tech entrepreneurship and insignificant for low-tech entrepreneurship.

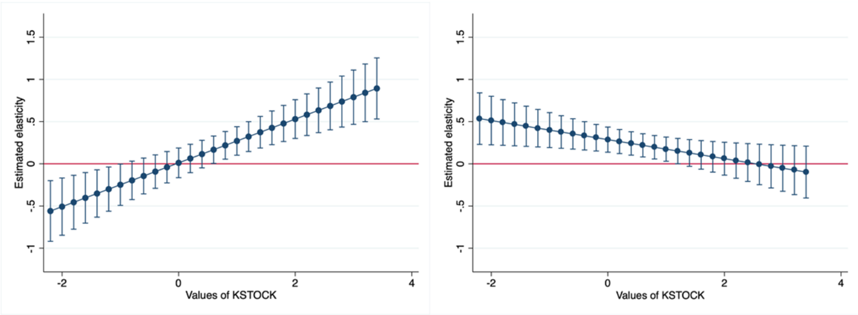
Table 5 IV-GMM results

	(1)		(2)	
	High-tech		Low-tech	
$INCUMB_{i,t\text{-}3}$	1.044***	1.051***	1.016***	1.013***
	(0.0123)	(0.0120)	(0.0105)	(0.0102)
$PC\_GDP_{i,t\text{-}3}$	−0.0324	−0.149*	−0.540***	−0.489***
	(0.0812)	(0.0895)	(0.0790)	(0.0760)
$ENTRY\_EXIT_{i,t\text{-}3}$	0.0785**	0.104**	0.127***	0.116***
	(0.0393)	(0.0411)	(0.0342)	(0.0348)
$LABOR\_PROD_{i,t\text{-}3}$	0.524***	0.585***	0.658***	0.630***
	(0.139)	(0.148)	(0.124)	(0.126)
$IMPORT\_RATE_{i,t\text{-}3}$	0.0362***	0.0375***	0.0225**	0.0219**
	(0.0112)	(0.0120)	(0.0108)	(0.0102)
$EXPORT\_RATE_{i,t\text{-}3}$	−0.0241*	−0.0187	−0.0288**	−0.0312**
	(0.0145)	(0.0148)	(0.0140)	(0.0126)
$FIN\_RISK_{i,t\text{-}3}$	0.0109	0.00474	−0.00414	−0.00142
	(0.0107)	(0.0113)	(0.00945)	(0.00957)
$MANUF\_SH_{i,t\text{-}3}$	−0.00190	−0.00894	0.0761***	0.0792***
	(0.0311)	(0.0295)	(0.0292)	(0.0250)
$KSTOCK_{i,t\text{-}3}$	0.0831***	−0.209***	0.0556***	0.185***
	(0.0155)	(0.0669)	(0.0144)	(0.0568)
$ENTROPY_{i,t\text{-}3}$	0.111	0.0112	0.244***	0.288***
	(0.0911)	(0.0897)	(0.0677)	(0.0761)
$ENTROPY_{i,t\text{-}3} \times KSTOCK_{i,t\text{-}3}$		0.259***		−0.115**
		(0.0587)		(0.0498)
_cons	−7.157***	−6.142***	−1.341**	−1.790***
	(0.577)	(0.683)	(0.577)	(0.580)
N	1022	1022	1022	1022
First-stage F-statistics	756.9	609.8	746.6	691.4

IV-GMM estimates. Robust standard errors in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. All specifications include NUTS2 region fixed effects and time dummies. All regressors are lagged three years and log-transformed

5.2 Skills

One may argue that the effect of diversity is insignificant in high-tech entrepreneurship because a majority of foreign residents in Italy originate from emerging and developing countries, and as such they may not play a direct role in expanding high-tech entrepreneurship in their host regions. Indeed, depending on their levels of skills, the ability of foreign entrepreneurs and workers to grasp knowledge spillovers and entrepreneurial opportunities may vary. In this spirit, other studies have pointed at a direct role of the diversity of high-skilled immigrants in promoting entrepreneurship, productivity and innovation in the host economies (e.g., Cooke &



a. High-tech entrepreneurship **b. Low-tech entrepreneurship**

Fig. 3 The moderating effects of knowledge stocks on cultural diversity—IV-GMM results. The figures report the estimated elasticities of high-tech and low tech entrepreneurship on KSTOCK for different values of ENTROPY estimated from IV-GMM estimates including interaction effects between the two variables

Kemeny, 2017; Suedekum et al., 2014; Trax et al., 2015). Hence, in what follows, we study whether the effects of diversity depend on the level of skills of the immigrants that we consider.

This endeavour faces some data limitations. Data about the educational attainment of foreign-born residents by country of origin can only be retrieved from the Census (hence, for 2011 only) and are only available at the NUTS 2 instead of NUTS 3 level. Hence, to impute a diversity index by skill level for foreign residents, we assume that the skills distribution of immigrants remains stable over time and is similar across NUTS 3 regions located within the same NUTS 2 region. Relying on this assumption, we impute the immigration stocks by skills as follows. From the 2011 Census data, we retrieve the share of immigrants of nationality c in NUTS 2 region r that have attained a given level of education, primary, secondary or tertiary. Then, for each year and province in our sample, we impute the number of people with a given level of education based on their nationality-specific shares. Suppose, for instance, that the share of German residents in NUTS 2 region r having attained a tertiary level of education is 30% according to the Census, and that there are one hundred German residents in NUTS 3 region i (within NUTS 2 region r) in year t. The imputed number of German residents with a high-level of education for province i at time t will be 30, that is $30\% \times 100$. Finally, drawing on the imputed residents by skill level, we can compute skill-specific entropy indices (see Colombelli et al., 2020, for a similar procedure).

We label the entropy index computed specifically for under-tertiary educated immigrants as *ENTROPY_L_EDU*, and for tertiary educated immigrants as *ENTROPY_H_EDU*, respectively. Applying this procedure to the imputed immigration stocks that we employ to construct the instrument, we can also construct an instrument for high- and low-skilled diversity. To shed light on the role of skills in explaining high- and low-tech firm formation, we replace the baseline entropy indices with these skill-specific entropy measures.

Table 6 Robustness check: Diversity effects by skills levels

	(1)		(2)	
	High-tech		Low-tech	
$KSTOCK_{i,t\text{-}3}$	0.0731***	−0.350***	0.0571***	0.387***
	(0.0167)	(0.135)	(0.0150)	(0.122)
$ENTROPY\_H\_EDU_{i,t\text{-}3}$	0.559**	0.401	−0.123	0.0437
	(0.233)	(0.264)	(0.215)	(0.254)
$ENTROPY\_L\_EDU_{i,t\text{-}3}$	−0.106	−0.146	0.293***	0.285***
	(0.123)	(0.128)	(0.0970)	(0.0987)
$ENTROPY\_H\_EDU_{i,t\text{-}3} \times KSTOCK_{i,t\text{-}3}$		0.124		−0.233*
		(0.128)		(0.119)
$ENTROPY\_L\_EDU_{i,t\text{-}3} \times KSTOCK_{i,t\text{-}3}$		0.160*		0.0249
		(0.0844)		(0.0652)
N	1022	1022	1022	1022
First-stage F-statistics	710.5	674.2	734.5	735.9

IV-GMM estimates. Robust standard errors in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. All specifications include the full set of control variables, as well as NUTS2 region fixed effects and time dummies. All regressors are lagged three years and log-transformed

Table 6 reports the IV-GMM estimates yielded by this exercise. Although the results should be taken with some caution given the above-discussed data limitations, they provide relevant insights. Rather intuitively, the results of the non-interacted models reported in columns 1 and 3 of Table 5 show that the cultural diversity of highly educated immigrants increases high-tech but not low-tech entrepreneurship. Instead, low-tech entrepreneurship increases in the diversity of lower-skilled immigrants.

In Fig. 4, we display the results obtained when adding interaction effects, which correspond to the estimates in Columns 2 and 4. Although adding interactions reduces the precision of the estimates, Fig. 4a clearly shows that, for high-tech entrepreneurship, the effects of cultural diversity are always increasing in the knowledge stocks. The main difference lies in the starting value, which is much higher for skilled cultural diversity. In other words, high-skilled cultural diversity has a positive effect on high-tech entrepreneurship irrespective of the knowledge stocks; instead, lower-skilled cultural diversity requires the moderating role of knowledge to trigger high-tech entrepreneurship.

Turning to low-tech entrepreneurship, decomposing lower- from higher-skilled cultural diversity shows that the substitution effects detected above are driven by the diversity of higher-skilled immigrants. Instead, the diversity of less skilled immigrants has a fairly stable effect on low-tech entrepreneurship. The finding that high-skilled cultural diversity interacts with knowledge while low-skilled does not suggests that, in context with a low level of knowledge, higher-skilled migrants may resort to low-tech entrepreneurship as a way to escape unemployment, while the effects of less skilled cultural diversity are more demand- than supply-driven and

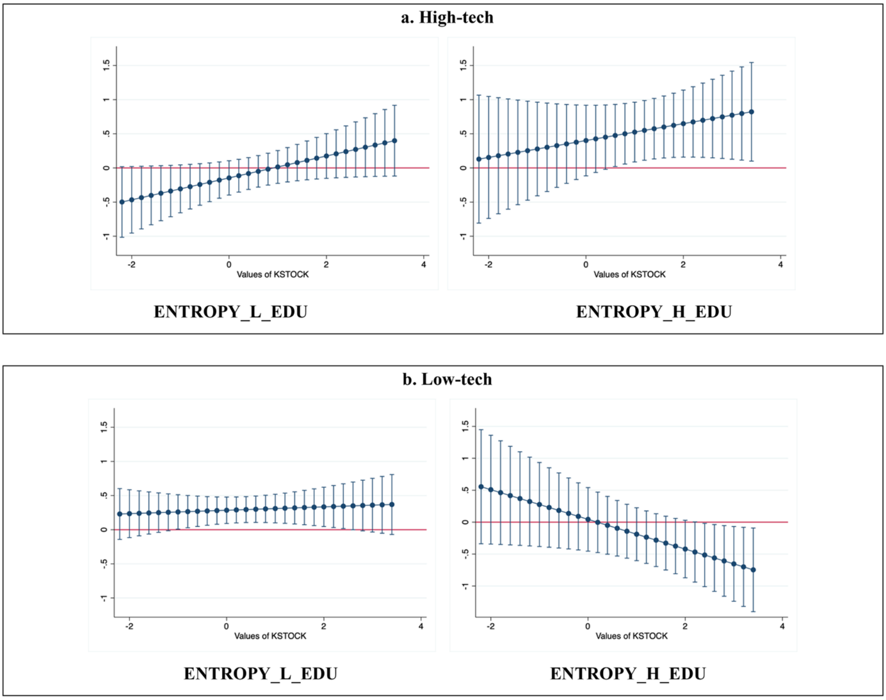


Fig. 4 Robustness check: The moderating effects of knowledge stocks on cultural diversity for different skills levels. The figures report the estimated elasticities of high-tech and low tech entrepreneurship to ENTROPY_L_EDU, ENTROPY_H_EDU for different levels of KSTOCK estimated from IV-GMM estimates including interaction effects between the two variables

so appear independent from the level of knowledge available in the external context. The latter interpretation is consistent with Hypothesis 2.

On the whole, distinguishing between high-tech and low-tech entrepreneurship sheds light on different channels through which diversity and knowledge may interact regionally. The magnifying effects of knowledge stocks on high-skilled diversity support our hypothesis that cultural diversity amplifies the variety of perspectives through which prospective entrepreneurs perceive unexploited opportunities emerging regionally. At the same time, we identify substitution between knowledge and diversity for low-tech entrepreneurship, which are driven by high-skilled immigrants' diversity and are suggestive of alternative channels, i.e., demand and necessity entrepreneurship, underlying the complex effects of diversity on Italian entrepreneurship.

In a further robustness check that we report in Appendix Table 8, we estimate our models separately for firm formation in high-tech manufacturing (HTM), knowledge-intensive services (KIS), low-tech manufacturing (LTM) and less knowledge-intensive services (LKIS). Consistent with the above interpretation, we find that knowledge stocks positively moderate cultural diversity in both high-tech sectors, i.e., high-tech manufacturing and knowledge-intensive services. Moreover, the estimated effects of diversity are on average more positive in knowledge-intensive sectors than high-tech manufacturing: the range of values of KSTOCK for which diversity has a positive effect is much broader for KIS than HTM—in other words, a lower level of knowledge is sufficient to trigger positive effects of diversity on KIS entrepreneurship.[6] Intuitively, KIS activities may be more reactive to the effects of diversity than HTM due to their generally lower levels of capital requirements.

As for low-tech industries, we estimate significant negative moderating effects of knowledge on low-tech manufacturing (LTM), while LKIS entrepreneurship is positively related with diversity but does not display significant interaction effects. Again, this points to the interpretation that the main channel intervening for the effects of diversity on LTM entrepreneurship, arguably requiring comparatively higher skills, may be necessity entrepreneurship, while the main driver for LKIS may be demand.

6 Conclusions

Focusing on narrowly defined geographic units of analysis, our study confirms the positive and significant association between cultural diversity and entrepreneurship. We argue that these dynamics can be interpreted in the light of the knowledge spillover and absorptive capacity theories of entrepreneurship and innovation. Our results support the interpretation that diverse economic agents perceive and value potential market opportunities differently, increasing the probability that unexploited business ideas are realized.

Our study contributes to the literature in studying the moderating roles of knowledge stock on the effects of cultural diversity on entrepreneurship. Our results suggest that the effects of cultural diversity on high-tech entrepreneurship are magnified by the knowledge stocks. This is in line with the interpretation that cultural diversity has a stronger effect on entrepreneurship in local systems marked by larger absorptive capacity. The diversified knowledge inputs provided by a culturally diverse population are more effectively converted to commercial purposes in regions that, because of their greater knowledge stocks, are better able to grasp the potential business relevance of these inputs. Our results indicate that the effect of diversity on high-tech entrepreneurship changes from negative to positive if the per-capita knowledge stock increases from the level of the province with the smallest level to the one with the greatest.

In the case of low-tech entrepreneurship, we find a positive effect of cultural diversity but a negative moderating effect of knowledge stocks. We interpret this result as evidence that in these sectors cultural diversity offers low-tech business opportunities, likely driven by unsophisticated demand for diverse products, to necessity entrepreneurs which become less and less appealing as the knowledge stock of the region increases. Therefore, the creation of start-ups should not be a goal in itself

[6] The main effect is insignificant for both, but it is positive and rather large for KIS and negative for HTM.

(Colombelli et al., 2016; Shane, 2009) since it can lead to 'defensive and necessity entrepreneurs' in local context characterised by low levels of knowledge.

Our results suggest that existing regional policies that aim at creating an environment favorable to innovation through investment in human capital and technology do not only directly affect entrepreneurship but also allow for benefiting more from cultural diversity. Moreover, policymakers should promote measures that ease access to knowledge to the migrant population, among which language and vocational training programmes targeted to newly arrived immigrants, and scholarships aimed at broadening access to higher education. To further support these dynamics, the regional policy mix could also try to alleviate the barriers to entrepreneurship that might be higher for immigrants, especially the financial and institutional ones.

If not properly regulated, the positive feedback at the local level between the knowledge stock and cultural diversity in high-tech sectors points to the risk of polarization in local development trajectories. The ability to exploit the synergies between diversity and knowledge for entrepreneurship, that nurture further immigration, diversity, and knowledge creation, may place more or less diverse and knowledge-rich regions on increasingly divergent paths. These self-sustaining dynamics may drive an increasingly knowledge-based upgrading in some regions that coexists with stagnation and risk of lock-in in other regions. Hence, our results support the importance of public support to knowledge creation in disadvantaged regions not only in its own right but also as a factor that facilitates a chain of further effects, primarily in boosting the effects of cultural diversity.

Appendix

See Tables 7 and 8.

Table 7 Summary statistics decomposed into between and within components

Variable		Mean	Std. dev.	Min	Max	Observations
$HIGH\text{-}TECH_{i,t}$	Overall	500.1477	719.6371	47	5665	N = 1022
	Between		710.9437	62.18182	4783.273	n = 93
	Within		130.6207	− 770.3068	1766.693	T-bar = 10.9892
$LOW\text{-}TECH_{i,t}$	Overall	1198.911	1382.112	155	9581	N = 1022
	Between		1376.515	179.8182	8024.364	n = 93
	Within		181.2149	− 831.4527	2755.547	T-bar = 10.9892
$INCUMB_{i,t}$	Overall	10.67393	.7138441	9.080687	13.07776	N = 1022
	Between		.7167121	9.097949	12.99699	n = 93
	Within		.0407711	10.42512	11.08804	T-bar = 10.9892
$PC\_GDP_{i,t}$	Overall	10.00202	.2608468	9.437046	10.75698	N = 1022
	Between		.254868	9.505541	10.70613	n = 93
	Within		.0624272	9.764741	10.17954	T-bar = 10.9892
$ENTRY\_EXIT_{i,t}$	Overall	− .0191168	.1719767	− .8509251	.5797268	N = 1022
	Between		.0840411	− .227159	.2788253	n = 93
	Within		.1502856	− .824395	.4554863	T-bar = 10.9892
$LABOUR\_PROD_{i,t}$	Overall	3.999994	.1200568	3.674621	4.334147	N = 1022
	Between		.1154114	3.747667	4.286624	n = 93
	Within		.0356872	3.829127	4.122784	T-bar = 10.9892
$IMPORT\_RATES_{i,t}$	Overall	− 1.952346	.9578299	− 4.921381	.7207391	N = 1022
	Between		.9331695	− 4.35058	.4100121	n = 93
	Within		.2391822	− 3.953476	.6412635	T-bar = 10.9892
$EXPORT\_RATES_{i,t}$	Overall	− 1.836545	1.127621	− 5.617557	.2758723	N = 1022
	Between		1.110606	− 5.38997	− .1095042	n = 93
	Within		.2301433	− 3.11258	− .8872757	T-bar = 10.9892
$FIN\_RISK_{i,t}$	Overall	.8534068	.7131765	− 1.75102	3.004849	N = 1022
	Between		.3570847	− .1786521	1.593146	n = 93
	Within		.6184454	− 1.565963	2.738195	T-bar = 10.9892
$MANUF\_SH_{i,t}$	Overall	− 1.75608	.4426833	− 2.869156	− .9233781	N = 1022
	Between		.4395515	− 2.770304	− .9915273	n = 93
	Within		.0706395	− 1.951159	− 1.477564	T-bar = 10.9892
$KSTOCK_{i,t}$	Overall	1.286785	1.098468	− 1.99384	3.492253	N = 1022
	Between		1.095443	− 1.413851	3.124166	n = 93
	Within		.1475241	.1627165	1.749565	T-bar = 10.9892
$ENTROPY_{i,t}$	Overall	1.065821	.1136397	.6257361	1.281054	N = 1022
	Between		.1076082	.7633651	1.272411	n = 93
	Within		.0382213	.8856988	1.309339	T-bar = 10.9892

Table 8 Robustness check: Separated analysis by type of entrepreneurship

	High-tech manufacturing		Knowledge -intensive services		Low-tech manufacturing		Less knowledge-intensive services	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ENTROPY_{i,t-3}$	−0.121	−0.269	0.127	0.0332	0.164	0.297**	0.259***	0.282***
	(0.158)	(0.174)	(0.0915)	(0.0897)	(0.120)	(0.127)	(0.0678)	(0.0782)
$KSTOCK_{i,t-3}$	0.129***	−0.303**	0.080***	−0.193***	−0.044**	0.345***	0.086***	0.149**
	(0.0277)	(0.130)	(0.0155)	(0.0669)	(0.0214)	(0.0950)	(0.0138)	(0.0583)
$ENTROPY_{i,t-3} \times KSTOCK_{i,t-3}$		0.384***		0.243***		−0.346***		−0.0604
		(0.114)		(0.0587)		(0.0834)		(0.0512)
N	1022	1022	1022	1022	1022	1022	1022	1022
First-stage F statistics	229.4	182.1	742.7	610.8	424.1	311.7	677.7	655.9

IV-GMM estimates. Robust standard errors in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. All specifications include the full set of control variables, as well as NUTS2 region fixed effects and time dummies. All regressors are lagged three years and log-transformed

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