WHAT DETERMINES ENTREPRENEURIAL CLUSTERS?

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Abstract
We contrast two potential explanations of the substantial differences in entrepreneurial activity observed across geographical areas: entry costs and external effects. We extend the Lucas model of entrepreneurship to allow for heterogeneous entry costs and for externalities that shift the distribution of entrepreneurial talents. We show that these assumptions have opposite predictions on the relation between entrepreneurial activity and firm-level TFP: with different entry costs, in areas with more entrepreneurs firms' average productivity should be lower; with heterogeneous external effects it should be higher. We test these implications on a sample of Italian firms and unambiguously reject the entry costs explanation in favor of the externalities explanation. We also investigate the sources of external effects, finding robust evidence that learning externalities are an important determinant of cross-sectional differences in entrepreneurial activity. (JEL: D24, D62, J23)

1. Introduction

There is a vast literature linking a country's endowment of "entrepreneurship" with economic prosperity. Environments where entrepreneurs can emerge easily are propitious to the creation of firms, their growth and their success. These ideas date back to Marshall (1890) and Schumpeter (1911). For example, the latter sees the entrepreneur as the carrier of innovation and hence the true engine of growth. But if entrepreneurship is so central to economic development, what drives it? Why are there so many entrepreneurs in some areas, such as Silicon Valley, and so few in others? Do these differences simply reflect differences in opportunities driven by, say, the presence of Stanford University? Why do we find these clusters in some countries rather than

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others, and in particular areas within countries, such as in the Italian industrial districts or the Ruhr? These important questions have often been in the forefront of policy debate and government intervention.

To answer these questions, one must address the choice of becoming an entrepreneur. Perhaps the best known model of entrepreneurship is that of Lucas (1978), explaining who in a given population will become an entrepreneur using differences in exogenously given individual talents. In Lucas, "talent" is identified with the ability to extract output from a given combination of inputs. Thus, more talented individuals are those who can obtain a higher total factor productivity (TFP) if they start a business. Since individuals with more talent make more profits, they will choose to be entrepreneurs. But what can explain clusters if we do not believe in genetic differences, i.e., if the distribution *at birth* of individual ability is the same across populations?

In this paper we extend the Lucas model to investigate two potential explanations of differences in entrepreneurial density across locations: entry costs and external effects. One possibility is that there are heterogeneous costs of entry, and the locations with lower costs of setting up a firm end up with more entrepreneurs and more firms because even relatively less talented individuals will find it profitable to start a business there. This is the approach implicitly followed by the large literature that focusses on factors—particularly financial—that keep the would-be entrepreneur from actually creating a new firm. Banerjee and Newman (1994), for instance, show that credit constraints can lead to poverty traps since potential entrepreneurs cannot invest in profitable occupations involving set-up costs. It is well documented empirically that limited access to financial markets can hinder the emergence of entrepreneurs.[1] More recently it has also been shown that regulation-induced high costs of entry hamper firm and employment creation (Bertrand and Kramarz 2002; Fonseca, Lopez-Garcia, and Pissarides 2001; Klapper, Laeven, and Rajan 2006).

The second possibility is that the distribution of individual productivity is shifted by local factors, for instance because of differences in learning opportunities, knowledge spillovers or intermediate input variety. A vast body of literature has pointed out that local externalities are an important determinant of firms' performance.[2] Externalities can be introduced in the Lucas model as shifters of the distribution of talents that make individuals more productive on average and therefore increase the share of agents that choose to start a business.

We show that the two assumptions have very different implications regarding the relation between the propensity of individuals to become entrepreneurs and their

1. Evans and Jovanovic (1989) show that wealthier individuals who are currently employees are more likely than the less wealthy to become self-employed, a finding consistent with liquidity constraints. Blanchflower and Oswald (1998) show that liquidity constraints affect the decision to become an entrepreneur even after controlling for individual ability. More recently, Guiso, Sapienza and Zingales (2004a) using individual level data for Italy find that in areas with a higher degree of financial development it is more likely that individuals become entrepreneurs, the rate of firm creation is higher, and there are more firms per inhabitant.

2. See for example the contributions in the *Handbook of Regional and Urban Economics*, Vol. 4 (Henderson and Thisse 2004).

average productivity. Under entry costs differences, in areas with lower entry costs (i) there should be more entrepreneurs and, (ii) their firms' average TFP should be lower. Thus, in equilibrium there should be a negative correlation between firm density in a given location and their TFP. On the contrary, with externality differences, in places with stronger externalities average entrepreneurial ability is higher and there are more entrepreneurs. In contrast to heterogeneous entry costs, the model with heterogeneous externalities implies therefore that in equilibrium there should be a positive correlation between the share of entrepreneurs in a given location and their firms' TFP.

We test these implications on a sample of Italian firms belonging to different clusters. There is substantial evidence that Italian entrepreneurs are very likely to start a business in the area where they were born, while workers are more mobile (Michelacci and Silva 2007). We therefore define actual entrepreneurs as firms active in a given location, potential entrepreneurs as individuals born in such location, and construct "entrepreneurial incidence" (EI) as the ratio of these two variables. We find that the data unambiguously reject the entry costs story and support the externality story: areas with a higher EI are characterized by a higher average productivity. More generally, a higher EI goes together with a rightward shift of the ability distribution. We also find that a firm's TFP is positively correlated not only with the overall EI (that is, computed using the total number of active firms), but also with sectoral EI (computed using the active firms at the sectoral level). This is further evidence in favor of externalities, which are well known to have a strong sectoral character (Cingano and Schivardi 2004). This should not lead to the conclusion that entry costs are necessarily the same across locations and play no role. Rather, (i) *alone* they cannot explain differences in entrepreneurial density and (ii) differences in shifters of the distribution of entrepreneurial talents are required to account for the pattern in the data.

Based on these results, in the reminder of the paper we corroborate the interpretation of the positive correlation between density and quality in terms of externalities. Following Marshall (1890) and the literature on agglomeration economies, and in particular Duranton and Puga (2004), we identify three different channels through which agglomeration may affect firms' productivity: first, the opportunities to learn from other firms, either because of knowledge spillovers or through learning entrepreneurial abilities from the observation of other firms; second, the size of the local work force, which can increase the division of labor and the quality of job–worker matches; and third, a greater variety of intermediate inputs. To discriminate between these three sources of externalities we run a horse race by constructing proxies for each one, computed at the local-sectoral level. As a proxy for learning opportunities and knowledge spillovers we use the number of firms in a location, the idea being that more firms offer more learning points; we proxy job-matching opportunities with the size of the local workforce; intermediate inputs variety is measured by the ratio of intermediate inputs to value added at the local level. We find strong evidence for the first channel, supporting evidence for intermediate inputs variety, and very weak or no evidence for externalities generated by labor pooling. In fact, the correlation between TFP and the number of firms proves to be extremely robust to a variety of controls. We further corroborate our interpretation of the number of firms in terms of learning and knowledge spillovers. Following an idea of Ciccone and Hall (1996), to address potential endogeneity concerns we instrument the number of firms with the local population in 1861, obtaining very similar estimates to the OLS ones.

This paper relates to three strands in the literature. First, it is connected with the entrepreneurship literature: we sort out two alternative explanations of clusters. Second, it contributes to the agglomeration literature: we investigate the sources of local externalities. Finally, it is related to the productivity literature: we provide evidence that differences in firm-level TFP may be due to the differing ability of entrepreneurs, which in turn could depend on the degree of learning spillovers.

Our results bear important policy implications. First, consistent with McKenzie and Woodruff (2006) for Mexico, we de-emphasize entry costs in explaining regional differences in entrepreneurial activity, adding an important element to the debate on the barriers to entrepreneurship. Second, our findings indicate that the density of firms might be a fundamental driving force of local externalities. This result is not confined to Italy: Henderson (2003) finds a positive effect of the number of plants at the local level on productivity in the United States.

The reminder of the paper is organized as follows. Section 2 sets out a simplified version of the Lucas model with exogenous factor prices, extended to incorporate the cost of setting up a firm. Exogenous and geographically heterogeneous costs of setting up a firm are a simple way to generate clusters. We then introduce the possibility that the original distribution of talents can be shifted by a local externality and compare the predictions of this model with those of the set-up-costs model. We then empirically contrast a number of testable predictions from these two models, using Italian firm-level data matched with firm cluster information as described in Section 3. Section 4 presents our basic results, showing that, contrary to the pure set-up-costs model but in agreement with the externality model, the distribution of entrepreneurial ability is rightward shifted where EI is higher. In Section 5 we explore the nature of the externality behind the positive correlation between the mass of entrepreneurs and their quality, finding evidence for a learning externality. Section 6 summarizes and concludes.

2. The Model

We use a modified version of the Lucas (1978) model of entrepreneurial ability. The economy consists of N regions; in each region a unit mass of individuals are born; each individual decides whether to become an entrepreneur or an employee. We assume that entrepreneurs can only set up a firm in the location where they were born, while workers are fully mobile.[3] While complete entrepreneurial immobility is clearly extreme, the fact that entrepreneurs are less mobile than employees and tend to start their business where they were born finds widespread empirical support. Michelacci and Silva (2007)

3. We thank one referee for suggesting this modeling strategy.

document that, in Italy, the share of entrepreneurs starting a business in the locality where they were born is substantially higher than the corresponding share of employees who work where they were born. Their argument is that becoming an entrepreneur requires some location-specific "relational" capital. A survey of a sample of Italian firms located in industrial districts, run by the Bank of Italy in 1997, shows that in more than 95% of the cases the firm owner, often the founder and manager of the firm, was born in the district where the firm is located, suggesting that entrepreneurs' location choice is dictated mostly by birth. Casual evidence also suggests that this is not only a feature of small businesses but extends to owners of very large firms: the Agnelli family was born in Turin and have their business, Fiat, there; Berlusconi was born in Milan and has his business in Milan; Ferruzzi was born in Ravenna and housed his business in Ravenna; Pesenti was born in Bergamo and headquartered his business there. The list could continue. On the other hand, the assumption that workers are perfectly mobile, while untenable over the short run, is a good characterization of the steady-state equilibrium, to which our model and empirical analysis apply. In the long run, migration flows respond to systematic differences in local labor markets. Indeed, one of the main features of Italy's post-war development was a massive migration flow from the South to the North. As a consequence of full worker mobility, in the long run there is a common national wage rate. Again, this is in line with the institutional setting of the Italian labor market, characterized by centralized bargaining, that greatly reduces wage differentials across areas.

Full factor mobility implies that we can confine the analysis to one representative region, taking factor prices w and u as given. We will discuss how to close the model at the end of this section. Individuals are born with different levels of entrepreneurial talent x, drawn from a random variable $\tilde{x}$ distributed according to a distribution function $\gamma(x)$ over the support $(\underline{x}, \bar{x})$, $0 \leq \underline{x} < \bar{x} \leq \infty$, with corresponding cumulative distribution function $\Gamma(x)$. Output is produced according to the production function $xg[f(n,k)]$, where f is a constant returns to scale function and g is a concave transformation. Following Lucas, we interpret this as the span of control. Define $\phi(r) = f(n,k)/n$, where $r = k/n$. The first-order conditions for an entrepreneur who maximizes profits can be written as

$$\frac{\phi(r) - r\phi'(r)}{\phi'(r)} = \frac{w}{u} \tag{1}$$

$$xg'[n\phi(r)]\phi'(r) = u \tag{2}$$

from which it is immediately evident that the capital/labor ratio does not depend on x. The above FOCs give two equations in two unknowns, which can be solved implicitly to obtain two-factor demand functions in terms of entrepreneurial ability: $n(x)$, $k(x)$. It is immediately verifiable that $n'(x) > 0$ and $k'(x) > 0$.

2.1 Start-up Costs

We modify the basic Lucas model by introducing a start-up cost c which has to be paid when becoming an entrepreneur. The profits of an entrepreneur of ability x before the entry cost are

$$\pi(x) = xg[n(x)\phi(r)] - n(x)[w + ur]. \tag{3}$$

Using the optimal input choices from conditions (1) and (2), we obtain $\pi'(x) = g[n(x)\phi(r)] > 0$: the profits of an entrepreneur are increasing with ability. An individual becomes an entrepreneur if $\pi(x) - c \geq w$. Given that, under standard regularity conditions, $\pi(x)$ is increasing and continuous, and that $\pi(0) = 0$, there exists one and only one value z at which the "marginal" individual is indifferent between being an entrepreneur and an employee:

$$\pi(z) - c = w, \tag{4}$$

which implicitly defines the ability threshold value $z(c)$ above which it is optimal to become an entrepreneur. In this economy, the mass of workers (who might or might not work in the same location as where they were born) will be $\Gamma(z)$ and that of entrepreneurs $(1 - \Gamma(z))$. By differentiating (4), we find that

$$\frac{dz}{dc} = \frac{1}{\pi'(z)} > 0. \tag{5}$$

The higher the start-up cost, the greater the ability of the marginal entrepreneur.

How can this model generate different levels of entrepreneurial activity across regions? A first possibility is that regions differ in terms of entry cost c, perhaps because of differences in bureaucratic costs due to disparate efficiency of the public administration. Areas with lower costs will have a larger share of entrepreneurs:

$$\frac{d(1 - \Gamma(z))}{dc} = -\gamma(z)\frac{dz}{dc} < 0. \tag{6}$$

Define the average entrepreneurial quality as the expected value of x conditional on being an entrepreneur:

$$E[x \mid x \geq z] = \frac{\int_z^{\bar{x}} x\gamma(x)\,dx}{1 - \Gamma(z)}. \tag{7}$$

When c rises, the quality of the marginal entrepreneur increases, hence so does average entrepreneurial quality:

$$\frac{dE[x \mid z]}{dc} = \frac{(E[x \mid z] - z)\gamma(z)}{1 - \Gamma(z)}\frac{dz}{dc} > 0, \tag{8}$$

where, to facilitate notation, $E[x \mid z]$ stands for $E[x \mid x \geq z]$. The inequality follows from the fact that $dz/dc > 0$ and $E[x \mid x \geq z] > z$, where the last inequality formalizes the notion that the marginal entrepreneur z is of lower quality than the average. Equations (6) and (8) imply that if differences in the share of entrepreneurs across locations are explained by entry costs, we should expect a negative correlation between the share of entrepreneurs and their average quality.

We can obtain additional implications of heterogeneity in entry costs for the distribution of entrepreneurial ability. Define $\Omega(y \mid z)$ as the cumulative density function of the random variable obtained by truncating x at z:

$$\Omega(y|z) = \begin{cases} \dfrac{\Gamma(y) - \Gamma(z)}{1 - \Gamma(z)} & \text{if } y \geq z, \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

$\Omega(y \mid z)$ is the share of entrepreneurs below any given level of ability y. As c increases, this share falls:

$$\frac{d\Omega(y \mid z)}{dc} = -\frac{\gamma(z)(1 - \Gamma(y))}{(1 - \Gamma(z))^2} \frac{dz}{dc} < 0. \tag{10}$$

This implies that heterogeneous entry costs induce a positive correlation of the share of entrepreneurs below any given level of ability with the overall mass of entrepreneurs, and a negative correlation above that level.

Summing up, heterogeneity in entry costs generates two sharp predictions: a larger mass of entrepreneurs should be associated with (i) a lower overall quality and (ii) a larger (smaller) share of entrepreneurs below (above) any quality level.

2.2 Local Externalities

A second potential reason for different levels of entrepreneurial activity across locations is that the distribution of entrepreneurial skills is different, due in particular to local externalities. For example, in some locations the diffusion of knowledge and ideas is facilitated by environmental factors. As shown by Jovanovic and Rob (1989), the easier the circulation of knowledge, the higher entrepreneurial quality. To model this possibility and derive its implications, we assume that the distribution of talent is parameterized by a shift factor λ, specific to each location: $x \sim \gamma(\cdot, \lambda)$, with $\Gamma(x, \lambda)$ representing the cumulative distribution function. The parameter λ measures the intensity of local externalities. We assume that $\partial\Gamma/\partial\lambda < 0$: λ shifts the probability distribution to the right in the first order stochastic dominance sense. In this setting, clusters arise in areas with high λ:

$$\frac{d(1 - \Gamma(z, \lambda))}{d\lambda} = -\frac{\partial\Gamma(z, \lambda)}{\partial\lambda} > 0. \tag{11}$$

Equation (11) implies that the higher is λ, the larger is the share of individuals with a given talent above the threshold z, and so the larger is the mass of entrepreneurs.

As before, we define average entrepreneurial quality as the expected value of x conditional on being an entrepreneur. This value will now depend on λ:

$$E[x \mid z, \lambda] = \frac{\int_z^{\bar{x}} x\gamma(x, \lambda)\, dx}{1 - \Gamma(z, \lambda)}. \tag{12}$$

The effect of a change in λ on average entrepreneurial quality is

$$\frac{dE[x \mid z, \lambda]}{d\lambda} = \frac{\int_z^{\bar{x}} x \frac{\partial\gamma}{\partial\lambda} dx - E[x \mid z, \lambda] \frac{\partial(1-\Gamma(z,\lambda))}{\partial\lambda}}{1 - \Gamma(z, \lambda)}. \tag{13}$$

Given that the first term is positive[4] and the second negative, this expression cannot be signed a priori. In fact, an increase in λ has two contrasting effects on average ability: on one hand, for given z, it shifts ability to the right, i.e., it increases average ability; on the other hand, some agents that would have been employees for a lower λ now become entrepreneurs. Given that they enter at the lower end of the talent distribution, more "entry" implies that quality is diluted, thus reducing average quality—the second term in square brackets in (13). The sign of $dE[x \mid z, \lambda]/d\lambda$ depends on the shape of the distribution of talents and on how λ parametrizes it. However, $dE[x \mid z, \lambda]/d\lambda > 0$ holds for a general family of distributions: the log-concave distributions (Barlow and Proschan 1975).[5] This family of distributions includes, among others, the uniform, the normal and the exponential. For such distributions, a positive correlation between the share of entrepreneurs and their average quality will emerge.[6]

The same reasoning applies to the distribution of entrepreneurial talents conditional on $x \geq z$, $\Omega(x \mid z, \lambda)$: as before, while not determined a priori, the mass of entrepreneurs with talent below (above) an arbitrary threshold y, $\Omega(y \mid z, \lambda)$, can decrease (increase) with the density of firms. Therefore, with externalities, under mild conditions on the distribution function Γ there is a positive relation between the overall share of entrepreneurs and their quality. Needless to say, differences in λ across locations do not necessarily reflect differences in externalities, but in any factor that may shift the distribution of abilities. A natural example is differences in the cost of acquiring entrepreneurial abilities on top of the talent one is naturally endowed with—that is, differences in the cost of learning entrepreneurial skills. We will return to this point in the empirical analysis.

2.3 Closing the Model

To close the model, we need to determine equilibrium factor prices. We assume that capital is infinitely elastically supplied at the world interest rate u. The wage rate has to equate total labor demand and supply. We close the model for the general case in which locations can differ both in entry cost c_i and in the distribution of talents $\Gamma(x, \lambda_i)$. Given the wage w, labor demand in location i is

$$L_i^D(w) = \int_{z_i(c_i, w)}^{\bar{x}} n(x, w)\, d\Gamma(x, \lambda_i), \tag{14}$$

where, from (4), z depends both on the wage rate and on the entry cost. Local labor supply is $L_i^S(w) = \Gamma(z(c_i, w), \lambda_i)$ - the fraction of those born in i that choose to

4. Using the property of first-order stochastic dominance, it can be shown that $\int_z^{\bar{x}} x(\partial\gamma/\partial\lambda)dx > 0$. In fact, for $d\lambda > 0$, stochastic dominance implies that $\int_z^{\bar{x}} x\gamma(x, \lambda + d\lambda)\, dx > \int_z^{\bar{x}} x\gamma(x, \lambda)\, dx$. Grouping terms and taking the limit for $d\lambda \to 0$ delivers the result.

5. A function h is said to be log-concave if its logarithm $\ln h$ is concave, that is if $h''(x)h(x) - h'(x)^2 \leq 0$.

6. The log-normal, traditionally used to model firm size (Steindl 1990) and income distribution (Harrison 1981), does not satisfy this property. Some simulations indicate that even for this distribution the above condition will generically be satisfied, implying that average ability increases with the share of entrepreneurs.

become workers. Under the usual regularity conditions on the production function and smoothness of the distribution of talents, it is immediate to show that z and n are decreasing and continuous in w. Therefore, L^D is also decreasing and continuous, $L^D(0) = \infty$, $L^D(\infty) = 0$, and L^S is increasing and continuous. Summing labor demand and supply over the N locations, we obtain the equilibrium condition:

$$\sum_{i=1}^{N} \int_{z(c_i,w)}^{\bar{x}} n(x, w)\, d\Gamma(x, \lambda_i) = \sum_{i=1}^{N} \Gamma(z(c_i, w), \lambda_i). \tag{15}$$

Given that continuity and monotonicity are preserved by the sum, there exists a unique w that equates total labor demand and supply.

To sum up, a model with different entry costs predicts a negative correlation between the density of entrepreneurs in different locations and their quality, while a model with externalities is compatible with a positive correlation. As a final remark, we stress that a positive correlation does not rule out that locations might differ in terms of entry costs. For example, in a location with low entry costs many firms will enter, which then might increase productivity through external effects. In fact, what a positive correlation rules out is that entry costs are the only or the most important source of differences in entrepreneurial density: other contrasting effects are needed to explain such correlation. We confront the implications of the models with the data in the subsequent sections.

3. Data Description

We test our propositions drawing on a dataset of Italian firms, the Company Accounts Data Service (in Italian, "Centrale dei Bilanci", CB), which provides standardized data on the balance sheets and income statements of about 30,000 Italian non-financial firms plus information on employment and firm characteristics. Data are collected by a consortium of banks interested in pooling information about their clients. A firm is included if it borrows from a bank in the consortium. The focus on level of borrowing skews the sample towards larger firms. Furthermore, because most of the large banks are in the northern part of the country, the sample has more firms headquartered in the North than in the South. Finally, since banks are interested in creditworthy firms, those in default are not included, so the sample is biased towards better-quality borrowers. Despite these biases, previous comparisons with population moments indicate that the sample is not too far from being representative; moreover, it covers more than half of private sector sales (Guiso and Schivardi 2007). Table 1, Panel A, gives summary statistics on employment, value added and the stock of capital at constant prices for the 1991 CB sample comprising 15,837 observations; we use 1991 as the reference year for our regressions but check for robustness when all the available years (1986–1994) are used. Data are reported by industrial sector using a 10-industry classification; to avoid the usual problems of estimating productivity in services we have restricted

TABLE 1. Descriptive statistics for 1991.

Panel A: Firms' characteristics (CB data)

Industry		VA	EMP	K	β	α	No. obs.
1	F	4856	96	9891	.63***	.39***	1367
		(20727)	(397)	(35821)	(.005)	(.066)	
2	T&C	2823	83	4287	.58***	.37***	2196
		(8183)	(230)	(10282)	(.003)	(.035)	
3	L&F	1659	54	1611	.62***	.43***	773
		(2652)	(93)	(3042)	(.005)	(.091)	
4	W&C	1786	56	3130	.70***	.35***	1110
		(2487)	(68)	(5918)	(.005)	(.077)	
5	T&Gl	4036	87	9854	.67***	.37***	1190
		(10981)	(201)	(37443)	(.005)	(.080)	
6	BM	6723	162	17499	.60***	.33***	666
		(47871)	(1109)	(118693)	(.007)	(.057)	
7	Mach	4487	112	5739	.72***	.28***	5262
		(27909)	(463)	(42705)	(.002)	(.012)	
8	Chem	7448	129	14878	.70***	.29***	1892
		(27959)	(461)	(79981)	(.004)	(.044)	
9	P&P	4454	92	7404	.72***	.32***	934
		(15941)	(306)	(29249)	(.005)	(.039)	
10	TEq	21021	595	38613	.70***	.26(*)	447
		(174741)	(5172)	(382168)	(.008)	(.144)	
	Total	4840	114	8433			15837
		(37277)	(969)	(80014)			

Panel B: Number of firms by LLS-industry (INPS data)

Industry		Average	S.D.	Max	Min	Total
1	F	62.5	89.7	722	1	25819
2	T&C	150.5	270.4	2501	2	43784
3	L&F	94.6	173.7	1159	1	13254
4	W&C	89.3	148.3	1529	2	27830
5	T	38.2	53.8	391	1	14001
6	BM	21.1	48.6	374	1	4224
7	Mach	234.2	568.0	8392	1	91606
8	Chem	44.4	113.1	1636	1	13785
9	P&P	71.5	221.4	2556	1	15634
10	Teq	13.0	21.2	166	1	2353
	Total	478.4	1121.4	2	17962	261549

Note: Value added (VA) and the stock of capital (K) are in thousands of euros (at 1991 prices). α is the capital coefficient and β the labor coefficient, both estimated using the Olley and Pakes (1996) procedure. Standard errors in parentheses. *** indicates significance at 1%, ** at 5%, and * at 10%. Sectoral classification: F = Food, beverages and tobacco; T&C = Textiles and clothing; L&F = Leather and footwear; W&C = Wood, products of wood, and cork; T&Gl = Timber, construction materials, and glass; BM = Basic metals; Mach = Metal products, machinery, and equipment; Chem = Rubber, plastic, and chemical products; P&P = Paper, printing, and publishing; TEq = Transportation equipment.

the analysis to manufacturing.[7] The capital stock is constructed using the permanent inventory method with sectoral deflators and depreciation rates, see Cingano and Schivardi (2004) for details.

We complement the CB data with another dataset on Italian industrial clusters, the Local Labor Systems dataset. The territory of Italy has been divided by the National Statistical Institute (ISTAT) into 784 local labor systems (LLS) on the basis of working-day commuting areas.[8] The idea behind the algorithm is to define self-contained labor markets in terms of worker mobility. Since the Data Services gives the firm's LLS code, we can match firms with the corresponding LLS. The number of manufacturing firms in the LLS is obtained from the files of the Italian Social Security Administration (INPS) on the population of firms with at least one employee for the years 1986–1998. With respect to the CB, the information on firms is much less detailed: for example, output is not reported so that TFP cannot be computed. For our purposes, the database contains the number of employees, the sector, and the location of each firm, from which very precise measures of entrepreneurial density at the local and sectoral level can be constructed. Panel B of Table 1 shows summary statistics on the average number of firms per LLS (as well as the total in the last column) for each of our 10 industries. It is clear that there is considerable sectoral and geographical variation in the clustering of industry: for the whole manufacturing, there are 478 firms per LLS with a standard deviation almost three times the mean (1,121) and range of 1–17,962.

3.1 Measuring Entrepreneurial Incidence

The model has a series of predictions relating the share of potential entrepreneurs that actually become active $(1 - \Gamma(z))$ and the distribution of their ability x. We now construct the empirical counterpart of this share, which we name entrepreneurial incidence (EI). We have assumed that people are born in a LLS and decide to become entrepreneurs there or employees anywhere in the country. Therefore, the correct empirical counterpart of this theoretical construct is the number of entrepreneurs in a location as a share of the "population at risk", which is given by the total number of individuals currently alive that were born in such location, independently from their current LLS of residence.

To get this measure we rely on the 1991 census which contains data on the municipality where each individual alive in 1991 was born. We select all the individuals in the 1991 census aged 20–65 (our definition of working age) and aggregate them according to the LLS where they were born. This procedure only leaves out from

7. As will become clear in the next section, the sectoral classification balances the need for homogeneity of the production technology and that of a sufficient number of sectoral observations to properly estimate TFP.

8. Even if defined using the same criteria (commuting ties), the concept of LLS differs from U.S. Core Based Statistical Areas since there is no minimum population requirement. Hence, like the French *zones d'emploi*, the Italian LLS entirely and continuously cover the national territory. The average land-area is 384 square kilometers, with a population density of 188 inhabitants per square kilometer. Population ranges from 3,000 in the smallest LLS to 3.3 million in the largest.

the population of potential entrepreneurs those who migrated abroad, for whom no information is available. We then divide the total number of firms active in a given LLS (the entrepreneurs) by the number of individuals born there of working age. This is our measure of entrepreneurial incidence, EI. We use the 1991 measure of the population at risk also for the other years in our sample (1986–1994).[9]

EI varies greatly between LLSs, with a mean of 6.9 (number of firms per 1,000 born), a standard deviation of 6.3, a minimum of 0.12 and a maximum of 44.7. Figure 1(a) gives a visual picture of the geographical clustering of EI and its dispersion across LLS, divided into four quartiles. The densest clusters are mostly in the North, although there are several in the South. To make sure that our results are not driven by North–South differences, in our empirical analysis we always include geographical dummies. In Figure 1(b) we draw the map according to the number of firms. In this case, the North–South divide is weaker. There are in fact several central and southern LLS with a large number of firms, such as Rome, Naples, Bari, Palermo, and Cagliari. However, in terms of the population born there, the entrepreneurial density of such areas is lower arguably due also to the migration flows mentioned above.

3.2 Estimating Entrepreneurial Ability

In order to test the two alternative models described in Section 2 we need a measure of entrepreneurial ability. In Lucas, entrepreneurial ability is modeled as a shift in the production function: better entrepreneurs will get more output from any combination of inputs. Put this way, entrepreneurial ability is simply equivalent to a firm's TFP. If this were the only feature affecting a firm's TFP, Lucas's model might serve as the basis for a theory of TFP, or at least of its dispersion across firms. The main limit of this theory is that the dispersion is simply assumed and inherited from the differences in entrepreneurial ability, which is taken as given. Our model of externalities is one way of providing a basis for an endogenous explanation of firm-specific TFP and the determinants of differences in average TFP across locations. To compute the contribution of entrepreneurial ability to TFP we assume that a firm's TFP has two components: one is common to all firms in the same industry and depends on their specific technology; the second is firm-specific, and in the spirit of our model we assume it reflects the ability of the firm's entrepreneur.

To obtain an estimate of the TFP of firm i we assume that output is produced with a Cobb–Douglas production function of the form $Y_{si} = x_{si} A_s * K_i^{\alpha_s} L_i^{\beta_s}$, where s indexes the industry, Y is output, and K and L denote the stock of capital and labor services.

9. Municipality of birth is only available from the census, hence every 10 years. An estimate of the population at risk can in principle also be obtained for the years in our sample other than 1991. This could be done by updating the 1991 figures for the population at risk with data on birth and mortality rates at the level of the municipality. This would require a long time series of age-specific birth and mortality rates for each municipality starting in 1966, which are costly to obtain as they are not available on tape. Since in any case the working age population of those born in a municipality evolves very slowly, we have deemed the benefit of constructing a year-specific figure not worth the information gathering cost. We thank the National Statistical Institute (Istat) for granting us access to these data.

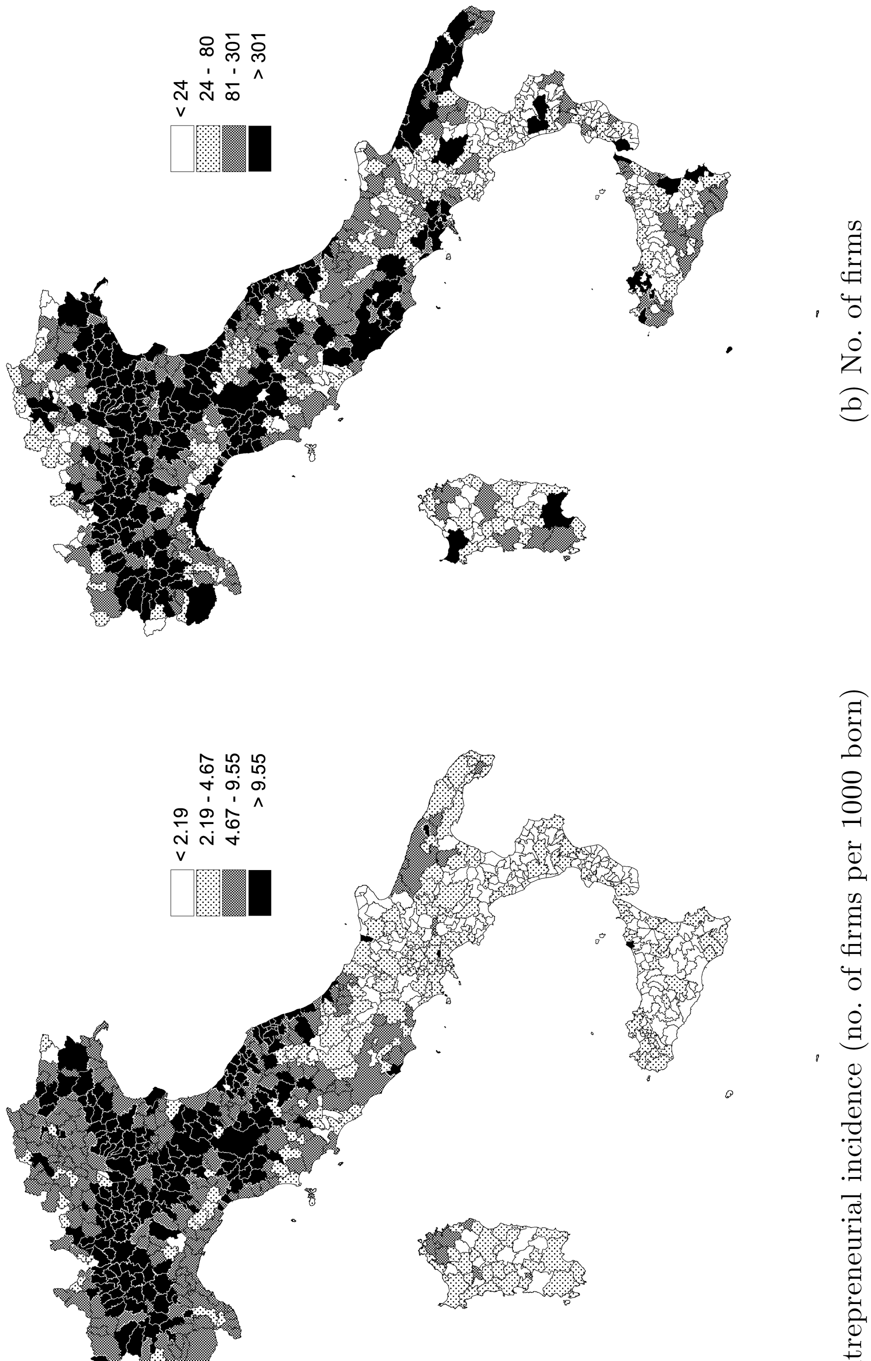

FIGURE 1. EI and number of firms in the Italian LLSs. (a) Distribution of EI (no. of firms per 1000 born), dividing the LLSs into four percentiles; (b) distribution of the number of firms, also split into four percentiles.

TFP is given by $TFP_{si} = x_{si} A_s$, and is the product of the sectoral component, A, and the firm-specific component, x. The latter is our measure of entrepreneurial ability. To obtain an estimate of TFP we need to compute values for α_s and β_s. To obtain estimates of the production function parameters that are robust to the endogeneity of some of the inputs (capital accumulation and labor demand may respond to unobserved productivity shocks) and the selection induced by exit (with some irreversibility, leaving the industry is more likely for firms with a lower capital stock when a bad productivity shock occurs) we use the multi-step estimation algorithm proposed by Olley and Pakes (1996), which accounts for both problems, allowing for consistent and unconstrained estimation of α_s and β_s.[10] To assess the reliability of the estimates, we have also calculated the coefficients using Solow's assumptions, finding similar results.

Table 1, columns (4) and (5), reports the estimated values of α_s and β_s. Production function estimates of $(\alpha_s + \beta_s)$ lie in the range 0.93–1.05. The model assumes decreasing returns to scale to avoid a degenerate equilibrium in which there exists only one firm supplying the whole market. Given that the capital coefficient is estimated using a semi-parametric procedure, we obtained its standard errors through a bootstrapping exercise based on 150 replications. As in Olley and Pakes (1996), standard errors are relatively large[11] and, given that the estimates of $(\alpha_s + \beta_s)$ are always somewhere around 1, the empirical model has no power to discriminate between different degrees of returns to scale. Formally, the null hypothesis $(\alpha_s + \beta_s) < 1$ is never rejected in a one-sided test even at the 10 per cent confidence level.[12]

Table 2 gives a first appreciation of the relation between EI and ability distribution (as well as other characteristics of the LLS), relative to the reference year 1991. We remove the industry-level component of our estimate of x with a first-stage regression of estimated TFP on a set of industry dummies. To account for possible outliers we drop observations in the first and last percentile of the ability distribution by year. The sample mean of entrepreneurial ability is 2.35 but there is considerable dispersion, as the high value of the standard deviation (0.5) implies. When the sample is split according to EI, entrepreneurial ability is substantially higher where EI is above median than where it is below median (2.38 compared to 2.16), which is inconsistent with the start-up cost hypothesis but not with heterogeneity in local externalities. The table also shows the share of firms with TFP below the 25th and above the 75th percentile both for the total sample and the two sub-samples of high-density and low-density areas. Contrary to the start-up cost model, there is a larger frequency mass to the left of the lower threshold in places with lower EI (40% in the low-density group compared with 22% among

10. To summarize, the procedure deals with endogeneity by approximating the unobserved productivity shocks with a non-parametric function of observable variables and for selection by introducing a Heckman-type correction term.

11. Pakes and Olley (1995) discuss the asymptotic properties of the estimator, suggesting that the bootstrapping procedure might overestimate the true standard deviation of the capital coefficient, partially explaining why its values are higher than those for labor.

12. Indeed, returns to scale might be initially increasing, due for example to fixed production costs, so that the "span of control" only kicks in for larger levels of operation. In fact, some small, yet growing firms might still be on the increasing part of the production function but, due to convex costs of adjusting the scale of operation, might not immediately exploit the full advantages of scale.

TABLE 2. Ability and other characteristics by Entrepreneurial Incidence.

Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
	Total sample		High EI LLS		Low EI LLS	
Ability	2.35	0.50	2.38	0.48	2.16	0.58
$I_{[\text{Ability}<25\%]}$	0.25	0.43	0.22	0.42	0.40	0.49
$I_{[\text{Ability}>75\%]}$	0.25	0.43	0.26	0.44	0.18	0.39
No. firms	5.18	1.41	5.94	1.10	4.42	1.28
Avg. firm size	2.28	0.51	2.48	0.33	2.08	0.57
No. workers	7.46	1.70	8.42	1.22	6.49	1.57
Intermediate inputs/VA	0.86	0.65	0.84	0.50	0.89	0.78

Ability, No. firms, No. workers and Intermediate inputs/VA are in log. High EI LLS are defined as EI above the median value by LLS. Ability is the log of TFP. $I_{[\text{Ability}<25\%]}$ is 1 if the ability is below the 25th percentile of the ability distribution and zero otherwise; correspondingly for $I_{[\text{Ability}<75\%]}$. Ability and intermediate inputs over value added are from the CB sample; the number of firms, of workers and average firm size are computed from the INPS dataset (the population).

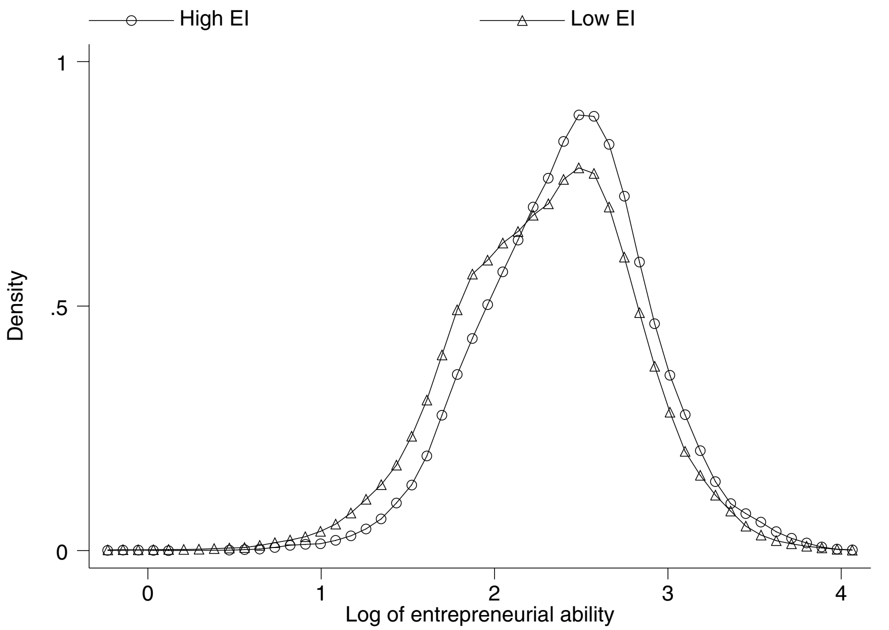

FIGURE 2. Distribution of log entrepreneurial ability for high (above the median) and low EI LLS.

the high-density locations), while, in accordance with the externalities hypothesis, the probability mass to the right of the upper threshold (the 75th percentile) is greater where there are more firms for given population born locally. Thus, the descriptive evidence clearly rejects the start-up cost theory in favor of heterogeneous shifters in the distribution of ability. The same conclusions can be drawn from Figure 2, which shows the distribution of entrepreneurial ability for firms in high-density and low-density LLSs, computed using Gaussian kernel non-parametric smoothers evaluated

TABLE 3. Firm efficiency and EI in the LLS.

	Panel A. Dependent variable: log TFP, OLS estimates					
EI_{TOT}	6.34***	7.56***	7.01***	3.95***	5.05***	4.50***
	(1.68)	(1.55)	(0.62)	(1.04)	(1.20)	(0.47)
No. obs.	15,837	27,173	137,907	15,837	27,173	137,907
	Panel B. Dependent variable: $I_{[\text{Ability}<25\%]}$, Probit estimates					
EI_{TOT}	−5.58***	−7.27***	−6.04***	−3.32***	−4.68***	−3.41***
	(1.17)	(1.12)	(0.41)	(1.09)	(1.06)	(0.44)
No. obs.	15,832	27,173	137,907	15,832	27,173	137,907
	Panel C. Dependent variable: $I_{[\text{Ability}>75\%]}$, Probit estimates					
EI_{TOT}	4.85***	5.26***	5.11***	3.26***	3.90***	3.69***
	(1.44)	(1.41)	(0.50)	(1.02)	(0.96)	(0.37)
No. obs.	15,837	27,173	137,907	15,810	27,173	137,907
Sample	CS	Firm Avg	Pool	CS	Firm Avg	Pool
Geo ctrl	MA	MA	MA	Prov	Prov	Prov

EI_{TOT} is the total number of firms over the total number of individuals born in the LLS. CS is the cross-section for 1991; Firm Avg is the firm average over time at the firm level after having de-trended all variables with a full set of year dummies; Pool is the whole sample with all firm-year observations. The geographical controls (Geo ctrl) are Macro Area (MA, 4 dummies) and Provinces (Prov, 103 dummies). All regressions include industry and time dummies. Standard errors adjusted for clustering at the LLS-year level. ***indicates significance at 1%, ** at 5%, * at 10%.

at 25 points over the range of x. Notably, the distribution of entrepreneurial ability is shifted to the right in areas with a high EI, implying that entrepreneurs in high-density areas have greater ability. In the following sections we refine this descriptive evidence using formal regressions and testing for statistical significance while controlling for potentially relevant factors. Table 2 also reports summary statistics for some of these controls, such as the number of firms, the number of workers, average firm size and the share of intermediate inputs over value added. Not surprisingly, in high-density areas there are more firms as well as more workers. More interestingly, the average firm size is larger in high EI areas, in accordance with the model's predictions that more able entrepreneurs demand more labor and set up larger firms because workers' mobility satisfies such demand.

4. Start-up Costs or Externalities? Testing the Two Models

According to equations (6) and (8), the start-up cost model implies that as we vary entry costs, entrepreneurial ability and the mass of entrepreneurs should move in opposite directions. Under reasonable assumptions, the heterogeneous externalities model implies a positive correlation between the two variables. Table 3 reports our basic test; the left-hand side is the log of our estimate of entrepreneurial ability at the firm level (x in the model); on the right-hand side we include EI ($1 - \Gamma(z)$ in the model). We also include as controls three geographical dummies for the Center, Northeast and Northwest of the country (the South is the omitted region). Given that the independent variable only varies across LLS-year, we use standard errors adjusted for clustering at this level. To check the robustness of our results, we use three different samples: a single cross section in 1991, which is the Census year when the locally born population is counted; the de-trended firm average over the entire period;[13] and the full 1986–1994 panel with year dummies. The first column shows the estimates using the 1991 cross-section; the correlation between EI and TFP is positive and statistically significant at 1%; to give a sense of its magnitude, moving from the 25th to the 75th percentile of the EI distribution results in an increase in TFP of 5%. Using firm averages and pooled data (columns (2) and (3)), the estimate increases slightly. This clearly contradicts the start–up cost model of business cluster formation already questioned by the previous descriptive evidence. This result is very robust across specifications.

One possible objection to these regressions is that macro areas might differ along several dimensions that affect both entry costs and firm performance. For example, Guiso, Sapienza and Zingales (2004b) have shown that the endowment of social capital, which might conceivably reduce entry costs and also increase average productivity, varies greatly across Italian provinces. To control for unobserved factors at the local level, we run the regressions including province dummies; this is a very fine geographical control as Italy is partitioned into 103 provinces, so that each is comprised on average by less than eight LLSs. This level of controls should account for most correlated geographical factors, including the social capital indicators developed in the literature, which typically vary by province. The estimated coefficient of entrepreneurial density is lower (3.95 compared to 6.34 in the cross sectional sample), an indication of possible spatially correlated effects, but still positive and statistically significant at 1% in all specifications. The effect of a shift from the 25th to the 75th percentile of the EI distribution is an increase in TFP of 3.3%.

The second panel of Table 3 sharpens the evidence on the validity of the start-up cost theory by looking at the relationship between the number of firms in a cluster and the share of them with ability below a lower bound or above an upper one. According to this model, there should be a positive (negative) correlation between the number of firms and the frequency of firms with ability below (above) a certain bound. The intuition is that as the start-up cost declines and the number of firms increases, the new entrants are of lower quality, so there is a larger (smaller) mass of entrepreneurs with ability below (above) any given threshold. To test this implication we set the lower bound at the 25th (and the upper at the 75th) percentile of the empirical distribution of ability and construct an indicator that is equal to 1 if the firm's specific ability is below (above) the threshold. We then run a probit estimate on the entrepreneurial share and the geographical controls. The first three columns of Table 3 show the results for the share below the 25th percentile for the three samples, using macro areas as geographical controls. They reveal a negative correlation with highly significant coefficients. This pattern is confirmed when provinces are used as geographical controls (last three columns). The last panel shows the share of firms above the 75th percentile, finding a positive coefficient of EI, highly significant in all specifications. Taken together, these

13. According to Bertrand, Duflo and Mullainathan (2004), the serial correlation in the independent variable can make inference problematic. As a simple solution, they propose to run estimates on the collapsed data ignoring the time series variation. We, therefore, first run a regression of firm-level TFP on a set of year dummies to clean for cyclical effects and then take the firm-level average.

findings suggest that a larger share of firms is associated with a shift to the right in the distribution of entrepreneurial talent. Thus, the two main implications of the start-up cost model are strongly rejected by the data. On the other hand, they are consistent with externalities, which (under mild conditions) not only predict a positive correlation between ability and the share of entrepreneurs, but also a negative correlation between the share of firms with ability below a lower bound and EI (and vice versa for the right tail).

In a series of unreported exercises we have performed additional robustness checks. First, our analysis is cast in a steady-state setting, so that we do not consider directly entry and exit. One could argue that specific patterns of entry and exit might be responsible for the correlation between the number of firms and average productivity that we find. To dispel this possibility, we have repeated the regressions including the entry and exit rates at the LLS level computed from the archives of the Italian Social Security Administration (INPS). We find that the estimates of EI are unaffected, while no clear cut relation emerges between TFP and exit and entry rates. Another potential concern is firm size. Traditionally, industrial districts are characterized by a network of small, efficient and connected firms (Guiso and Schivardi 2007). It could be that the correlation we find reflects the fact that small firms are more efficient and that EI is higher where firms are smaller (typically in industrial districts). Table 2 already suggests that this is not the case, as denser LLS have larger, not smaller average firm size. To further exclude this possibility, we have added average firm size in the LLS, finding again no significant change in the coefficient of EI and, if anything, a positive correlation between average firm size and TFP. This is also true at the individual firm level: we find that TFP is positively correlated with various measures of size, such as total assets and sales. The evidence in Table 3 is therefore unequivocal: it strongly rejects the theories of cluster formation based only on differences in entry and start-up costs, such as differences in the fixed costs or bureaucratic steps required to organize a firm. It lends support to models that emphasize differences in the distribution of entrepreneurial abilities, possibly due to local externalities.

To further strengthen our interpretation, we consider the correlation between EI and TFP at the local sectoral level. If differences in EI are due to entry costs, then they should apply independently of the sector of activity, so that the correlation should arise mainly at the aggregate level.[14] Instead, we should expect externalities to also have a sectoral component.[15] In fact, entrepreneurship entails some degree of sectoral specificity, so that not only the total EI should be positively related with TFP, but also density at the sectoral level. This is tested in Table 4, where we insert both the overall EI and the

14. This is not to say that entry costs are equal across industries. Rather, it means that if two locations differ in the level of such costs, the differential effect on EI should be uniform across industries. In any case, even if two locations differ in terms of entry costs at the industry level, the implication of a negative correlation between density and quality carries over at that level too.

15. There is a large literature on the relative importance of intra-industry and inter-industry spillovers, which has so far failed to reach a clear consensus, even if the intra-industry component tends to be important in most empirical studies (Rosenthal and Strange 2004). Using the same dataset as in this paper, Cingano and Schivardi (2004) find evidence in favor of intra-industry spillovers, and no evidence of inter-industry spillovers.

TABLE 4. Firm efficiency and EI in the LLS-sector.

	Panel A. Dependent variable: log TFP, OLS estimates					
EI_{TOT}	4.48***	5.56***	4.78***	2.00*	2.37**	2.02***
	(1.13)	(1.04)	(.40)	(1.09)	(1.06)	(.41)
EI_{SECT}	3.55	3.51*	4.03***	3.27**	4.15***	4.04***
	(2.47)	(2.05)	(.90)	(1.40)	(1.19)	(.63)
No. obs.	15,837	27,173	137,907	15,837	27,173	137,907
	Panel B. Dependent variable: $I_{[\text{Ability}<25\%]}$, Probit estimates					
EI_{TOT}	−4.77***	−6.90***	−5.70***	−1.93	−3.20***	−2.56***
	(1.12)	(1.01)	(.40)	(1.24)	(1.10)	(.47)
EI_{SECT}	−1.57	.66	−.62	−2.39*	−2.36*	−1.40***
	(1.84)	(1.73)	(.68)	(1.38)	(1.23)	(.56)
No. obs.	15,837	27,173	137,907	15,832	27,173	137,907
	Panel C. Dependent variable: $I_{[\text{Ability}>75\%]}$, Probit estimates					
EI_{TOT}	2.60**	2.75***	2.64***	1.04	1.09	1.09**
	(1.13)	(1.00)	(.39)	(1.25)	(1.12)	(.43)
EI_{SECT}	4.19**	4.30***	4.37***	3.61***	4.24***	4.14***
	(1.91)	(1.75)	(.61)	(1.32)	(1.14)	(.46)
No. obs.	15,837	27,173	137,907	15,810	27,173	137,907
Sample	CS	Firm Avg	Pool	CS	Firm Avg	Pool
Geo controls	MA	MA	MA	Prov	Prov	Prov

EI_{TOT} is the total number of firms over the total number of individuals born in the LLS, EI_{SECT} is the total number of firms in the LLS-sector over the total number of individuals born in the LLS. CS is the cross-section for 1991; Firm Avg is the firm average over time at the firm level after having de-trended all variables with a full set of year dummies; Pool is the whole sample with all firm-year observations. The geographical controls are Macro Area (MA, 4 dummies) and Provinces (Prov, 103 dummies). All regressions include industry and time dummies. Standard errors adjusted for clustering at the LLS-year level. ***indicates significance at 1%, ** at 5%, * at 10%.

EI at the sectoral level, i.e., calculated using the number of firms in an LLS-industry over the working age population born in the LLS. The first panel shows the results for the correlation between ability and the two indexes of entrepreneurial density. We find that both indexes are positively correlated with productivity. In particular, the overall EI has a larger and more significant coefficient in the specification with the macro area geographical controls, while the reverse occurs with provincial controls. This arguably reflects the fact that the overall EI is more strongly correlated with local attributes that are not fully captured by macro area dummies but are picked up by the finer geographical controls, while the sectoral EI reflects more direct external effects.

The second and third panels report the regressions for the probability that a firm's TFP is below the 25th percentile of the distribution (Panel B) and above the 75th percentile (Panel C). The pattern is very similar to that found in Panel A, with both indicators being significant in most specifications. All in all, the evidence points to a positive correlation between sectoral EI and productivity. This is consistent with the externalities hypothesis and at odds with the idea that some locations have more firms only because of lower start-up costs.

5. Which Externalities?

Up to now, we have used the model to obtain equilibrium correlations between EI and ability, without any causal interpretation. Empirically, we showed that the TFP distribution and EI display a positive correlation. We now take a further step and investigate the underlying factors that can explain the rightward shift in the TFP distribution. In practice, by log linearizing (12), we can immediately verify that this amounts to identifying some measurable factors that shift the entrepreneurs' ability distribution (the variable λ in the model) and to running a regression of (log) ability on the (log) indicator of λ. The logical candidate to explain productivity differences according to density is local externalities. In this section, therefore, we contrast different sources of externalities to look for more direct evidence that can sort out their nature.

There is a large theoretical literature on agglomeration economies (see Duranton and Puga (2004) for a recent survey). This literature has maintained the original Marshallian idea (Marshall 1890) that the spatial concentration of production can be beneficial for three reasons. First, concentration fosters the circulation of ideas and the possibility of learning from other agents. Second, a large concentration of workers in the same industry can have beneficial effects both in terms of the specialization that each worker can achieve and the quality of worker/job matches. Third, industrial clusters offer a wide variety of intermediate inputs, with potentially beneficial effects on productivity.[16] The empirical literature on the extent and scope of agglomeration economies suggests that localization economies are important. However, a consensus has not yet emerged on the relative merits of the different sources and investigation is continuing (see Rosenthal and Strange (2004) for an exhaustive assessment of the state of the empirical debate).

We distinguish among these different effects by proposing a proxy for each potential externality. To proxy for learning externalities we use the *number of firms* operating in a given industry and in a given location. According to Guiso and Schivardi (2007), this is the reference group within which information flows are most intense. If learning entrepreneurial abilities is not, as we think, a routine activity, then an obvious feature facilitating it is the number of firms in a given location. If learning takes place mainly on the job and on the site, a larger number of firms offers more (and better) opportunities to acquire entrepreneurial abilities, since a potential entrepreneur can compare different working practices and business ideas, possibly by working in different firms.[17] Moreover, the process of knowledge acquisition continues even after

16. Marshall (1890) wrote: "When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from neighborhood to one another. The mysteries of trade become no mysteries; but are as in the air, and children learn many of them unconsciously. . . . Employers are apt to resort to any place where they are likely to find a good choice of workers with the special skill which they require. . . . The advantages of variety of employment are combined with those of localized industries in some of our manufacturing towns, and this is a chief cause of their continued economic growth."

17. According to Saxenian (1994), the mobility of workers across firms and their acquired capacity to start up new firms was one of the main reasons behind the success of Silicon Valley during the technology boom. This would also be consistent with the model and the empirical evidence of Lazear (2005), according to which the probability of becoming an entrepreneur is positively related to the number of tasks a worker is previously exposed to, because the entrepreneur needs to be able to understand and coordinate different activities. Again, more firms could offer better opportunities of learning the complex set of skills required to manage a firm.

Table 5. Firm efficiency and externalities.

	Dependent variable: log TFP, OLS estimates								
No. firms	.051***	.046***	.048***	.031***	.024***	.028***	.0115	.018***	.019***
	(.009)	(.009)	(.003)	(.007)	(.006)	(.003)	(.009)	(.008)	(.003)
Int.Inputs/VA	.020	.063***	.028***	.009	.052***	.015***	.007	.046***	.006
	(.013)	(.011)	(.004)	(.011)	(.010)	(.004)	(.011)	(.010)	(.004)
Labor	−.007	−.001	−.005**	−.001	.004	.001	.005	.004	.002**
	(.005)	(.005)	(.002)	(.004)	(.004)	(.002)	(.005)	(.004)	(.002)
No obs.	15,837	27,173	137,907	15,837	27,173	137,907	15,837	27,173	137,907
Sample	CS	Firm Avg	Pool	CS	Firm Avg	Pool	CS	Firm Avg	Pool
Geo controls	MA	MA	MA	Prov	Prov	Prov	LLS	LLS	LLS

No. firms, Int.Inputs/VA, and Labor are in logs and computed at the LLS-industry level. CS is the cross-section for 1991; Firm Avg is the firm average over time at the firm level after having de-trended all variables with a full set of year dummies; Pool is the whole sample with all firm-year observations. The geographical controls are Macro Area (MA), Provinces (Prov) and Local Labor Systems (LLS). All regressions include industry and time dummies. Standard errors adjusted for clustering at the LLS-year level. ***indicates significance at 1%, ** at 5%, * at 10%.

the business is started, because knowledge spillovers on alternative technologies or new markets keep accruing in regions with a large population of firms. According to this interpretation, what matters for learning is the number of "data points" available, so that the relevant measure of spillovers is the *absolute* number of firms. This is different from the approach of the previous section, where we characterized the equilibrium correlation between the *share* of local born population becoming entrepreneurs and their ability distribution. The availability of intermediate inputs—the second reason why spatial concentration can raise firms' productivity—is easily measured by the ratio of intermediate inputs to value added at the local sectoral level. In fact, if greater concentration leads to higher productivity through more reliance on intermediate inputs,[18] we should find that TFP is positively related to this indicator. The third reason, the labor market pooling effect, is measured by the number of workers operating in a given LLS-sector. Summary statistics for these variables are reported in Table 2.

5.1 Main Results

In Table 5 we regress firm-level TFP on the number of firms, the share of intermediate inputs over value added and the number of workers, with all the variables computed at the LLS-industry level (all variables are in logs).[19] To save on space, in all the remaining tables we omit the probit results, which fully confirm those of the OLS.[20]

18. Using U.S. data, Holmes (1999) finds that sectoral concentration at the local level is positively related to intermediate input intensity, although the effect is rather modest.

19. While the number of firms and the number of workers can be computed from the INPS dataset, covering the respective populations, we have information on intermediate inputs and value added only for the CB sample, which is used to compute the measure of intermediate input intensity.

20. The interested reader can find them in a previous version of this paper (Guiso and Schivardi 2005).

With four spatial controls, we find that the number of firms has a positive and significant coefficient in all specifications, with a value of around 0.05. The share of intermediate inputs is not significantly different from zero in the cross-sections, but is significant when using averaged data and in the pooled data. Thus there are indications that the availability of intermediate inputs might also foster local productivity, though the evidence is less clear-cut than for the number of firms. The number of workers is never significant, save in one case. The exception is found in the pooled data with four spatial controls, and its negative coefficient is at odds with the idea that local externalities are attributable to labor market pooling effects. To give a sense of the magnitude of these effects, using the pooled estimate of column (3) we calculate that increasing the number of firms by one standard deviation would bring about an increase in firms' productivity of about 9%, which is quite large; doing the same with intermediate input intensity would increase TFP by a more modest 1.2%. The next three columns of Table 5 repeat the exercise with 103 spatial controls (the province dummies). The estimates for the number of firms and the intermediate inputs become somewhat smaller, but remain highly significant. The number of workers has no effect in any specification.

All in all, we conclude that the evidence supports both learning externalities and intermediate input variety, with the former playing a more prominent role. Controlling for these sources, no evidence of labor market pooling emerges.

5.2 Robustness and Further Implications

Having established that the number of firms is strongly correlated with firm-level TFP, we further investigate if we can correctly interpret this correlation as evidence in favor of learning externalities, as suggested above.

The OLS correlations face the endogeneity problem that plagues the empirical analysis of density and productivity. There could in fact be unobserved local factors causing both and not accounted for by our geographical controls, as even the finer ones (the province dummies) refer to wider areas than the Local Labor System. For example, politicians might care about places with a high production density and provide business-oriented public goods, such as infrastructure, which raise productivity. While the province dummies absorb some of these effects, the transfers could take place at an even finer geographical level, leaving the regression residual correlated with the number of firms. We address this issue in two ways. First, since our regressors vary with the LLS and the industry, we can exploit the cross-industry variation while inserting geographical controls at the LLS level. In the last three columns of Table 5 we report the same regressions as in the previous table, adding a dummy for each LLS. We find results that are similar to those of the previous columns with province dummies, losing significance only in the case of the cross-section sample. Indeed, in a similar vein, Henderson (2003) finds a positive and robust correlation between the number of

TABLE 6. Firm efficiency and firm number: OLS and IV regressions.

	Dependent variable: log TFP.					
No. firms	.030***	.030***	.029***	.035***	.019***	.025***
	(.004)	(.003)	(.001)	(.007)	(.006)	(.002)
No obs.	15,837	26,689	137,907	12,861	21,645	111,882
Sample	CS	Firm Avg	Pool	CS	Firm Avg	Pool
Est. Meth.	OLS	OLS	OLS	IV	IV	IV

The first three columns report OLS estimates; the fourth to sixth columns are IV estimates. The instrument used is the population in the LLS in 1861. The Number of firms is in log and computed at the LLS-industry level. Standard errors adjusted for clustering at the LLS-sector–year level. See Table 3 for the explanation of the specifications.

plants and productivity in the United States.[21] His findings therefore suggest that the correlation we find is not confined to Italy.

Second, we provide instrumental variables estimates. Following Ciccone and Hall (1996), we instrument the number of firms with the population at the LLS level in 1861 (the year of the first Italian census). Clearly, the larger the population in a given location, the larger the number of firms, even if the primitive distribution of abilities is the same across areas. Moreover, given that population density is persistent, it can be maintained that population in 1861 is correlated with the population today and thus with today's mass of firms. Indeed, a regression of the log of the number of firms at the LLS-industry level on the population in 1861 at the LLS level produces an R^2 of 0.4. On the other hand, it is reasonable that the local population size in the mid-19th century is not correlated with potential determinants of productivity in manufacturing over our sample period. This is our identifying assumption; it can be defended on the grounds that industrialization in Italy did not begin until the 1890s, and that the biggest wave of industrialization occurred in the 1950s. If we presume that location choices before the industrial revolution were dictated mainly by agricultural fertility, and that this has no obvious relation to productivity in manufacturing in the late 20th century, then the instrument satisfies the exogeneity condition.

Table 6 reports the results of a regression of firm efficiency on the number of firms in the LLS-sector, estimated by OLS (first three columns) and by IV (last three columns). For brevity, we only report the results when using provincial dummies as geographical controls. All the regressions indicate that OLS and IV estimates are highly similar, with no evidence of a systematic bias in the OLS regressions. This suggests that our geographical controls are fine enough to capture any local factor that affects firms' TFP and could be correlated with the number of firms in the area, lending support to our causal interpretation.

21. Henderson's paper belongs to the literature assessing the industrial scope of spillovers, i.e., whether they are within or between industries, and he uses the number of own-industry plants as a measure of industrial concentration. Given that he does not aim at separating different sources of externalities, unlike us he does not control for the alternative channels. In line with what we find, he claims that the number of plants is the most robust indicator of intra-industry spillovers, and interprets it as evidence of knowledge externalities.

We have also performed robustness checks along the industry dimension. First, the two-digit classification we use might be too coarse and mix industries with different characteristics. While a more refined analysis is difficult because of limited sample size, particularly in the estimation of the production function coefficients, we can increase the number of industry controls in the baseline regression. We have run the basic regression on the pooled data including 296 dummies at the four-digit level, finding no substantial difference in the estimates. A second problem is that we impose the same coefficient for the number of firms across different industries. While assessing learning opportunities at the industry level is beyond the scope of this paper, we have run a separate regression for each industry. In all industries we find that the number of firms has a positive and significant effect on TFP, with coefficients ranging from a low of 0.017 for basic metal to a high of 0.067 for leather and footwear. As a final check, we have added average firm size among the regressors, to insure that we are not simply capturing a higher efficiency of small firms. As in the case of EI, we find that such inclusion does not change the results, and that, if anything, average size is positively correlated with TFP.

6. Conclusions

This paper has compared two alternative theoretical models of cluster formation, one based on the cost of setting up a business and the other on local externalities. These models carry opposite implications on the sign of the correlation between entrepreneurial ability and entrepreneurial incidence, defined as the number of firms over the number of individuals born in a given location. This relation is negative if geographical agglomeration of firms is due predominantly to start-up costs and positive if agglomeration is driven predominantly by differences in externalities. The models also have clear-cut implications for the relation between entrepreneurial incidence and the frequency mass at the two tails of the ability distribution. We have confronted these theoretical predictions with data on a large sample of Italian manufacturing firms coupled with information on the geographical clusters to which the firms belong. We have found overwhelmingly that a model with only start-up costs is rejected and the externalities hypothesis is strongly supported.

When exploring the sources of externalities, we have found supporting evidence for intermediate input variety and especially for learning spillovers. We have indeed shown that the data agree with specific predictions of knowledge spillovers models. In future work we plan to investigate the modes through which these spillovers take place, focussing in particular on the possibility that in some locations it might be easier to accumulate entrepreneurial skills.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Experimental datasets (Zip archive).

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